Exporter Survival with Uncertainty and Experimentation*

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Abstract

Two facts distinctively separate exporter dynamics from firm dynamics. One is the strikingly low survival rate of new entrants into export markets. The second is that new entrants survive less than re-entrants. We argue that these two facts are particularly useful to discipline exporter dynamics models because many sources of firm heterogeneity (e.g. fixed costs) do not affect survival rates when firms time their entry decision optimally. We extend a standard exporter dynamics model by positing that firms experiment to resolve an uncertain component in foreign-market profitability. We estimate the model using customs data from Peru. Despite its parsimony, having only four relevant parameters, the model matches the survival profile of new entrants and re-entrants. It is also sufficiently rich to deliver predictions about many exporter dynamics facts highlighted in the literature. Finally, we exploit variation across products and markets to provide additional evidence supporting the model's experimentation mechanism.

JEL codes: F10, F12, F14

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1 Introduction

Countries worldwide dedicate considerable resources, mainly through export promotion agencies and foreign embassy services, to helping firms establish a sustained presence in foreign markets. Underlying these policies is the view that increasing the number of domestic firms capable of achieving sustained exports is vital to fostering aggregate export growth and economic development. Academic research supports this view, showing that a considerable fraction of aggregate exports is accounted for by firms that did not export a few years earlier (Eaton et al., 2008; Freund and Pierola, 2010; Lederman et al., 2011). However, the effectiveness of these policy efforts may falter as the dynamics of new exporters are still not well understood.

A growing body of literature has developed models of exporter dynamics by analogy to the closed-economy firm-dynamics literature, emphasizing sunk cost and fixed costs, learning, customer capital, and financial frictions.[1] Two facts, however, distinctively separate exporter dynamics from domestic firm dynamics. The first is that most new exports into a market do not become established export businesses (Eaton et al. (2008) and Ruhl and Willis (2017), among others). The second, documented in this paper, is that re-entrants survive more than first-time entrants. This fact is a core feature of exporter dynamics, given that re-entry in export markets is pervasive (Blum et al., 2013; Arkolakis, 2016).

In this paper, we argue that survival moments that condition on the time of market entry, such as these two facts, are particularly useful for disciplining models of exporter dynamics. The reason is that these moments are largely insensitive to time-invariant sources of heterogeneity that are critical for matching exporter cross-sectional facts, such as firm-specific demand or fixed costs in each export market (Eaton et al., 2011). The core insight is that variation in these features—for example, lower fixed costs—would not make a firm more successful than another in a given market; instead, it would lead the firm to start exporting earlier. By focusing on survival moments upon entry, we can learn about the dynamic forces that shape exporter behavior while remaining largely agnostic about time-invariant sources of heterogeneity. The same logic applies to any extensive-margin moment—i.e. any moment that depends on whether the firm actively exports at some point in time—that conditions solely on entry. By contrast, other facts about exporter dynamics, such as export growth or moments conditional on size, require taking a stand on the relationship between profits and sales and on the static components of firm profitability, respectively.

Guided by these two facts, we build a parsimonious model of exporter dynamics. The model combines a standard persistent process for firm profitability with firms optimally timing their entry into export markets, and uncertainty about foreign-market profitability that can only be resolved by actively exporting (Segura-Cayuela and Vilarrubia, 2008; Freund and Pierola, 2010; Albornoz et al., 2012; Nguyen, 2012; Cebreros, 2016; Eaton et al., 2025). More precisely, a firm is initially inexperienced in a given export market, with gross profits determined by an idiosyncratic time-varying component and a constant market-specific component. Operating in the market requires paying an

[1] See Alessandria et al. (2021a) for a survey.

idiosyncratic fixed cost, and firms can enter and exit freely. While exporting, inexperienced firms may receive a positive multiplicative profitability shock ψ, an event that occurs with intensity λ. After the shock occurs, the firm becomes experienced and remains so thereafter in that market. The shock ψ embodies two economic forces. First, by experimenting, the firm knows it may eventually become better at generating profits in the market; this is a learning-by-exporting component. Second, because ψ is stochastic, the firm is uncertain about how large that improvement will be.

A virtue of the model is its parsimony and tractability. In particular, the dynamic problem reduces to a single equation in a single unknown, allowing for a transparent characterization of the forces shaping exporters' behavior. Notably, the model delivers a sharp version of the invariance argument above: survival-upon-entry moments do not depend on market-specific profit shifters or fixed costs, but only on four common parameters. As a result, these four parameters can be estimated using only survival-upon-entry moments, without information about firm-specific heterogeneity or the probability distributions that generate it.

The model also provides a natural explanation for the two main facts. Since inexperienced firms may export at a loss to experiment, many receive only a small ex-post profitability boost and exit, which explains the low survival rates of new entrants. At the same time, many re-entrants have already resolved their uncertainty during their initial export spell, so they re-enter more conservatively and therefore survive longer. In addition, we show that it is the "uncertain," rather than the "learning-by-doing" component of experimentation, that explains this result. Indeed, we show analytically that if the magnitude of the profitability boost ψ—albeit not its timing—were known in advance, inexperienced firms would enter markets more conservatively than experienced firms, implying higher survival among first-time entrants, contrary to the data.

We estimate the model using firm-level customs data on Peruvian exports for the period 1993–2008, targeting the survival rates of first-time entrants and re-entrants. Despite its parsimony, the model does an excellent job matching these moments. Our estimates also indicate that firms learn quickly: a firm that continuously exports has a 23.1% probability of receiving the multiplicative shock within a month. The shock also exhibits considerable dispersion—its standard deviation is about 2.4 times the annual volatility of the underlying profitability process—which helps explain firms' willingness to experiment in foreign markets in the hope of realizing a favorable outcome.

A concern with the centrality played by experimentation in our model is that it is not a directly observable component of exporter behavior in our data. We take two steps to assess its empirical relevance. First, we exploit variation in two proxies for uncertainty: the type of products exported and the distance to the destination. If uncertainty is a key driver of the low survival rates of new entrants, survival should be lower in differentiated products and in destinations farther away, where uncertainty about market profitability is plausibly greater. These predictions hold in the data. Also, the expected variation in uncertainty by product type and by distance to the destination arises from re-estimating the uncertainty parameter for each subsample, holding all other parameters constant at their baseline estimated values. Second, we examine untargeted moments often studied in the exporter-dynamics literature. The model does an excellent job explaining a broader class of untargeted extensive-margin moments related to survival and re-entry. We then show that, under additional assumptions needed to map profitability into sales, the model does a reasonable job explaining facts related to export sales growth, as well as to survival and growth conditional on size.[2] The remaining mismatches are informative about additional model features that could help improve the model's performance regarding these facts.

Related Literature This paper belongs to an extensive literature on exporter dynamics, surveyed in Alessandria et al. (2021a). In particular, it is most closely connected to a strand of the literature that argues that demand uncertainty is a defining feature of export markets (Albornoz et al., 2012; Nguyen, 2012; Akhmetova and Mitaritonna, 2013; Timoshenko, 2015b; Li, 2018; Berman et al., 2019; Eaton et al., 2025). Similar to these papers, our model includes a market-specific uncertain component that can only be resolved by exporting. We contribute to this literature in three ways. First, we develop a new framework that is tractable enough to deliver novel analytical results while at the same time being sufficiently rich to generate quantitative predictions about the main exporter dynamics facts highlighted in the literature. In particular, we identify a large class of relevant moments in the data that only depend on four model parameters and are robust to time-invariant sources of heterogeneity à la Eaton et al. (2011). In this regard, our framework complements complex structural models in this literature—notably Eaton et al. (2025)—with an alternative approach that prioritizes parsimony. Second, we document a novel fact on the difference between the survival rates of first-time entrants and re-entrants. Our model implies that this fact provides sharp evidence supporting an experimentation mechanism that helps resolve foreign market uncertainty. Third, we provide additional empirical evidence on the relevance of experimentation in exporter dynamics by exploiting differences in survival rates across markets and products.

Another strand of the literature studies economies with a learning-by-doing mechanism where exporters get better during the first years of their export experience (Schmeiser, 2012; Timoshenko, 2015a; Ruhl and Willis, 2017; Alessandria et al., 2021b). Our model also features this channel, but it differs from these papers in that the size of the profitability improvement is uncertain. Importantly, we show analytically that a model where firms get better by exporting but the size of improvement is deterministic, rather than stochastic, would have counterfactual implications for survival probabilities, with re-entrants surviving less than first-time entrants.

Finally, we contribute to the literature on time-aggregation biases in export data by uncovering an additional source of bias on top of the well-understood partial-year effect (Bernard et al., 2017). Since survival rates are low, many exporters are close to the profitability threshold that makes exporting optimal, and thus spend part of the year—even years that are not the entry ones—out of the export market. As a result, the fraction of the year the firm is "active" in the export market varies substantially across firms, especially among small and young ones. We show that this margin is quantitatively relevant for many moments of exporter dynamics. For example, early in

[2]We assume CES demand to generate predictions on export sales growth, and assume no heterogeneity in the time-invariant parameters for predictions on moments conditional on size. See Section 6 for details.

their exporting experience, firms display a larger variance in their growth rates due to significant variation in the "fraction of time" within a given year that their profitability is above the export threshold.[3] Importantly, the partial-year effect is not only quantitatively relevant for growth rates (Bernard et al., 2017) but also for other exporter dynamics moments, such as survival rates, that do not depend on firm sales.

Outline The rest of the paper is organized as follows. Section 2 describes the two distinguishing facts about exporter survival that we emphasize in this paper. Section 3 sets up the model and derives predictions on survival probabilities. Section 4 estimates the model and presents the results. Section 5 tests for the uncertainty and experimentation mechanism of the model by looking at its implications across products and markets. Section 6 tests the model's predictions for untargeted moments commonly used in the exporter dynamics literature. Section 7 provides concluding remarks.

2 Two central facts about exporter survival

This section documents the two central facts about exporter survival that guide our analysis: the survival profile of first-time entrants is low and flat, and the survival profile of re-entrants is higher than that of first-time entrants. We measure these facts using shipment-level customs data from Peru. We begin by introducing the relevant definitions and basic data issues.

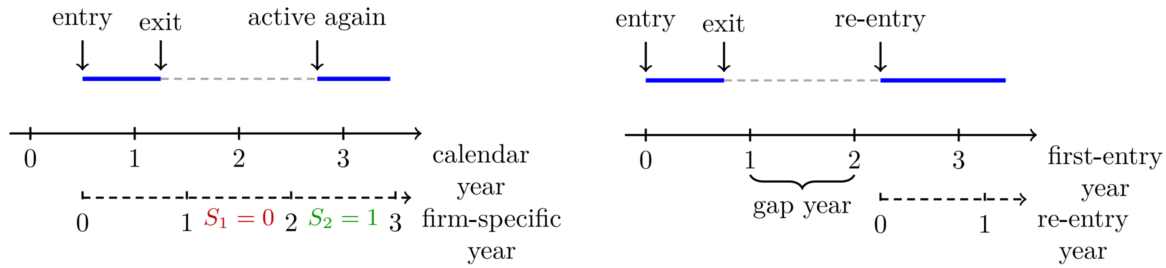
We employ firm-shipment level customs data from Peru for the period 1993-2008 graciously provided to us by the Trade and Integration Unit of the World Bank Research Department. The dataset was collected by this unit as part of their efforts to build the Exporter Dynamics Database described in Fernandes et al. (2016). It covers all export shipments from Peru between 1993 and 2008 by firm and destination country (i.e. export market).

We refer to the first entry of a firm in a given export market as an export "incursion". To address partial-year effects, we define firm-market-specific years. For every firm-market pair, the entry year starts on the date of the first shipment. For example, if a firm first exported to a market in June 3rd 1997, then the entry year is June 3rd 1997 - June 2nd 1998, the first year where we study survival is June 3rd 1998 - June 2nd 1999, and so on.[4] Panel (a) in Figure 1 illustrates our definition of a firm-market-specific year.

The survival rate at horizon T, denoted S_T, is the proportion of incursions that are active in the corresponding export market T years after entry. Importantly, our definition does not impose uninterrupted presence in export markets. In the example of Figure 1, the firm is inactive in horizon

[3] This new partial-year effect, which operates on the extensive margin, is closely connected to the decomposition of the intensive margin between number of shipments and sales per shipment (Alessandria et al., 2010; Kropf and Sauré, 2014; Hornok and Koren, 2015; Békés et al., 2017). Indeed, if the number of shipments is related to the amount of time a firm spends above the threshold, our model also has implications for this decomposition. See Appendix I for a formalization of this idea.

[4] In Appendix B, we present our main results using annual data based on calendar years. They are qualitatively similar; quantitatively, survival is larger during the first year due to the partial-year effect.



(a) Incursion and survival **(b)** Re-entry

Figure 1: Illustration of the definitions of incursion, survival, and re-entry

Notes: Panel (a) illustrates the definition of incursion and survival using firm-market-specific years. Panel (b) illustrates the definition of re-entry: after a gap of at least one first-entry year without exporting to a destination, a new export spell is classified as a re-entry, and re-entrant survival is then measured using years specific to that re-entry date.

1, but active again in horizon 2. This figure also illustrates the importance of our partial-year effect correction: without it, the firm would be classified as surviving every period, while in reality, there was a large gap in its export presence. We follow each incursion for up to five years, so the survival profile is the set of survival rates $\{S_T\}_{T=1,..,5}$. Since we do not observe data before 1993, we only consider incursions starting in 1997 to minimize the chances of falsely identifying as incursions export instances with an antecedent before 1993.[5] Also, since we track survival up to five years after entry, we restrict the sample to incursions starting no later than 2002.

If a firm does not maintain a continuous presence in the market after the original incursion, a later export spell may be classified as a re-entry. We define an export re-entry as the start of a new spell of exports to a destination by a firm that has exported to that destination in the past but not in the previous year, according to the "first-entry" firm years. This implies that at least twelve months must have elapsed between shipments for a shipment to be considered a re-entry. Once the re-entry is identified, we define "re-entry" years based on the timing of the first re-entry shipment to account for partial-year effects and make survival measures for first-time entrants and re-entrants comparable. Panel (b) in Figure 1 illustrates the definition. According to the first-entry firm-market-specific years, the firm is inactive in horizon 1. Thus, any subsequent shipment would be considered a re-entry. Because our definition of survival does not require continuous exporting, some observations may simultaneously contribute to first-time entrant survival and re-entrant survival. This can be seen in our example, where the same shipment appears in both timelines.[6]

[5]For example, incursions in 1997 would be false if the firm exported in the past but not in the last four years. Using the latest years in our database, we find the proportion of incursions that have exported in the past but not in the last four years to be 8.4%. As we consider incursions in later years, false incursions will arise only after a longer period of inactivity. For example, the proportion of false incursions is 3%(1%) when we firms are inactive for 7(10) years. Averaging across incursions in all years, we estimate the proportion of false incursions to be 3.3%.

[6]Here, we focus on the first re-entry of an exporter whose incursion we observe. We do this for consistency with the estimation in Section 4. The results are very similar using all re-entrants and with alternative definitions of re-entry, including those based on calendar years (see Appendix B and C.1, respectively).

Table 1: Descriptive Statistics

Year	Firms and Entries				Macro Variables		
	Firms	Incursions	Re-entries	Incursions: 2-year surv. (%)	Exports (US$ mill.)	GDP growth (%)	RER (%)
1997	3,775	4,081	0	23.6	6,825	6.5	2.3
1998	3,563	3,522	0	26.3	5,757	-0.4	4.1
1999	3,895	4,249	141	24.7	6,088	1.5	14.1
2000	4,017	4,537	348	22.3	6,955	2.7	2.7
2001	4,347	4,244	491	24.2	7,026	0.6	1.4
2002	4,685	4,222	679	24.7	7,714	5.5	1.7
2003					9,091	4.2	-1.1
2004					12,809	5.0	-2.8
2005					17,368	6.3	-1.8
2006					23,830	7.5	0.5
2007					28,094	8.5	-3.4
2008					31,018	9.1	-8.2
Total	11,064	24,855	1,659	24.2			

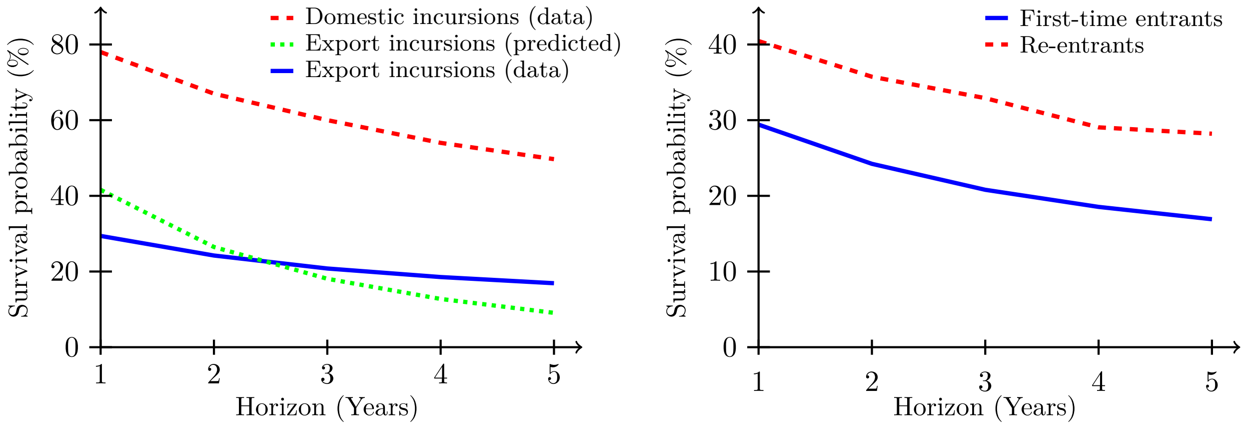
Notes: Left panel based on Peruvian customs dataset (World Bank). First two columns of right panel based on INEI. The real exchange rate (RER) multiplies nominal exchange rate by US PPI (BLS) and divides it by Peruvian CPI (INEI). GDP growth and RER are expressed in annual variation (%). A higher RER means a more depreciated Peruvian currency.

A potential concern with this re-entry definition is that some firms may be classified as re-entrants because of the natural frequency of shipments rather than because they truly exit and return. In Appendix C.1, we use shipment-level data to construct alternative definitions of re-entry based on the minimum time elapsed between consecutive shipments (12 months, 18 months, 24 months). The results presented below are robust to these alternative definitions.

Table 1 reports basic descriptive statistics for our sample, using annual data. During 1997–2002, we identify $24,855$ incursions by $10,071$ unique firms and $1,659$ first re-entries by $1,017$ unique firms. First-time entrants account for 8.8% of export value and 38.6% of export instances, while first-time re-entrants account for 1.1% of export value and 3.7% of export instances. The table also reports three macro indicators for Peru over 1997–2008: aggregate exports, GDP growth, and the real exchange rate. While our model does not account for changes over time in potential export profitability due to changes in the real exchange rate, by focusing on averages over a period that includes both appreciation and depreciation of the domestic currency, we hope to capture patterns in the data that approximate those that would arise in a fully stable macroeconomic environment.

Fact 1: The exporter survival profile is low and flat

Figure 2a shows the survival profile of export incursions in our dataset (blue-solid line). A striking feature of this profile is how low survival rates are. Only 29.4% of Peruvian export incursions are still active one year after entry. Five years after entry, the survival rate is 16.9%. Another



(a) Survival profile: Domestic vs. exporter

(b) Survival profile: First entry vs. re-entry

Figure 2: Two key facts of exporter dynamics

salient feature of the survival profile is the flat slope after $T = 1$. In contrast to the vast fraction of firms that exit just after entering the export market, further exit at longer horizons is considerably more gradual. For reference, Figure 2a displays the survival profile of U.S. domestic firms as production units (red-dashed line).[7] Compared to exporter survival rates, domestic survival rates are substantially higher. The first year after entry, 77.9% of U.S. firms in an entry cohort are still in operation. Five years after entry, the survival rate is 49.1%.

The slope of the exporter survival profile depicted in Figure 2a is not driven by compositional effects. Alternatively to the raw data used to display Fact 1 in the figure, we can obtain the survival profile by controlling for other covariates in a regression framework. The results are displayed in Table A.1. First, we regress the survival status of incursions in each of the first five horizons on horizon dummies (column 1). This exercise is equivalent to simply calculating the survival rate per horizon, as we did in the figure. Then, we add a set of fixed effects by product (2-digit Harmonized System) and destination-year (i.e. the country and year corresponding to the survival status).[8] We can see in column 2 that adding these flexible controls has a negligible impact on the estimated survival rates.

The fact that exporter survival rates are notoriously low is difficult to match for "traditional" exporter-dynamics models based on persistent profitability processes and sunk and fixed costs, especially once one also accounts for the flat slope of the survival profile. Figure 2a displays the survival profile predicted by the benchmark version of our model, in which the experimentation mechanism is removed (green-dotted line). Such a model can only match low survival with a

[7]Domestic survival rates are computed from entry-cohort data in the Business Dynamics Statistics (BDS) of the Bureau of the Census. For comparability with export survival rates, we restrict the sample to tradable-good producers (agriculture, mining, and manufacturing) in entry cohorts 1997–2004. The comparison is imperfect: domestic survival captures persistence as an employer, whereas exporter survival captures persistence as a seller in a specific market.

[8]Since years are firm-market specific, they involve more than one calendar year. Thus, for each firm-market incursion, we attribute the calendar year with the largest overlap.

sufficiently negative drift in profitability, which then implies a survival profile that is too steep, with survival rates that are too high early on and too low at longer horizons.

Although this benchmark model is a special case of our model, its inability to fit the exporter survival profile reflects a broader limitation of traditional exporter-dynamics models, a point already emphasized in the literature (see, e.g., Ruhl and Willis (2017)). For this reason, Fact 1 has been central to recent work on demand uncertainty and experimentation in exporter dynamics. Nevertheless, it is the novel fact we present next that, together with Fact 1, makes a substantially stronger case for the relevance of such models.

Fact 2: The survival profile is higher for re-entrants than for first-time entrants

Firms often temporarily cease to export only to re-enter the same market later. In our dataset, 20% of the incursions that exit a market re-enter that market within five years. Figure 2b compares the survival profile of (first-time) re-entrants (red-dashed line) with the profile for first-time entrants (blue-solid line). Re-entrants have uniformly higher survival rates. Most of the difference already occurs in the first year after entry, when the survival rate is 40.5% for re-entrants versus 29.4% for first-time entrants. Over longer horizons, this gap is preserved with only slight changes. Like Fact 1, Fact 2 is not driven by composition either. Columns 3 and 4 of Table A.1 display analogous results including re-entries. In column 3, we include horizon dummies for re-entrants, which delivers the survival rates depicted in Figure 2b. In column 4, we include a full set of dummies by product and destination-year. Again, we find that these controls for composition do not substantially affect the survival profiles depicted in the figure.

Fact 2 has no corresponding analogue in the firm dynamics literature. As a matter of fact, we are not aware of any study that has computed re-entrant domestic survival rates. A likely reason is that instances of domestic re-entry are much more infrequent than in the case of exports and are typically either dismissed as a nuisance or tinkered with assuming them as measurement error.[9]

These two facts are not specific to Peru. Using firm-level customs data, the World Bank team in charge of the Exporter Dynamics Database (EDD) replicated our two main findings, i.e. the low and flat survival rates of first-time entrants and the higher survival rates of re-entrants, across a broad set of emerging-market and low-income economies using the most recent updates to the data. Strikingly, the same patterns appear in each of the twenty-two countries examined (in addition to Peru), indicating that these are pervasive features of exporter dynamics (see Appendix C.2).[10]

[9]Due to how "entry" is defined in standard firm dynamic databases (Baldwin et al., 2002), recorded re-entry instances might be spurious. For example, the BDS reports that re-entry instances represent 7% of incursions. However, since the database only includes firms with at least one employee in its payroll, a large fraction of this percentage probably comes from transitions in and out of employer status (Jarmin and Miranda, 2002).

[10]While the underlying microdata are confidential and cannot be shared, the EDD team graciously provided us with the resulting tabulations, which we reproduce in Appendix C.2.

3 The model

In this section, we develop a partial equilibrium model of firm export behavior. For tractability, we assume that firms' export decisions are independent across markets.[11] Next, we study the firm's problem in a given market. To economize on notation, we avoid firm and market subindexes.

3.1 Set up

Firms go through two stages in their lifetime as exporters in a given market. At first, they are *inexperienced* (i) and earn flow profits

$$\pi_i(\theta_t) = \left\{ \begin{array}{c} \kappa\theta_t - F \text{ if export at } t \\ 0 \text{ otherwise} \end{array} \right\}$$

where θ_t is a time-varying index of profitability, $\kappa > 0$ is a constant profitability parameter, and $F > 0$ is a fixed cost. These three determinants of export potential are firm-market specific. For simplicity, we do not include entry sunk costs, so firms may exit and re-enter markets freely. As we argue in Section 4.3, sunk costs are not necessary to obtain the qualitative predictions of the model, nor do they help improve its quantitative predictions. Time-varying profitability follows a geometric Brownian motion (GBM),[12]

$$d \log \theta_t = \mu dt + \sigma dZ_t. \tag{1}$$

Firms are born with profitability $\bar{\theta} > 0$. $\mu, \bar{\theta}$ and σ are common across firms.[13]

Since all firms are born with $\bar{\theta}$, κ is an index of initial profitability in the market. For example, a high value of κ may capture a better ability to make product adaptations that match export market idiosyncrasies based on a prior understanding of the market's demand features (Artopoulos et al., 2013). This parameter may also capture an advantage in communicating or conducting transactions with foreign agents at lower variable trade costs, e.g. due to family ties. The fixed expenses F represent the costs incurred in activities such as sustaining a distribution network and conducting marketing efforts in the foreign market, which are paid on a continual basis while exporting.

For inexperienced firms, exporting yields additional benefits beyond receiving flow profits. Inexperienced firms know that their current profitability level in the export market is only transient

[11] In our model, this can be microfounded using CES demand, linear variable costs, no interdependence in fixed costs across markets, and independence across markets in the firm-market-specific shifter ψ introduced below. Interdependence in export decisions substantially increases the theoretical and computational complexity of the problem (see Albornoz et al., 2016 for an analytical example and Alfaro-Urena et al., 2023 for a quantitative model).

[12] The profitability parameter θ_t can be microfounded as the combination of random processes for demand and productivity jointly determined by a multivariate GBM in a stationary environment with CES preferences. See Luttmer (2007).

[13] We assume that the firm's discount factor satisfies $r > \mu + \frac{1}{2}\sigma^2$ so that expected profits are finite, which is satisfied by our estimated values. Furthermore, to guarantee the existence of a stationary distribution, we follow Arkolakis (2016) and assume that the mass of firms that are born at each instant grows at rate $g_B > 0$. We could also assume an exogenous death rate $\delta > 0$. However, δ would directly affect survival probabilities while g_B does not.

and that they will eventually become *experienced* if they keep exporting. More specifically, while exporting, inexperienced firms become experienced (e) with intensity λ. An experienced firm earns flow profits

$$\pi_e(\theta_t;\psi) = \left\{ \begin{array}{c} \psi\kappa\theta_t - F \text{ if export at } t \\ 0 \text{ otherwise} \end{array} \right\}$$

where ψ is a firm-market-specific profitability shifter that is absent in the case of an inexperienced firm. We assume $\psi \sim \text{Pareto}(\psi_m, \alpha)$. The scale parameter ψ_m governs the potential for profit scaling up when the firm becomes experienced. We assume $\psi_m \geq 1$, which implies that being experienced is always desirable. The shape parameter α is a key parameter in our model, as it governs the extent of uncertainty the firm faces. A lower value of α implies the distribution has a higher variance and a fatter tail.

A key feature of our model is that ψ is unknown ex-ante by inexperienced firms. This captures the fact that some sources of uncertainty are hard to unravel without actively participating in the targeted export market. For example, firms may be uncertain about the appeal of their products at the destination or their ability to engage the right distributors to push them in those markets (Eaton et al., 2025).

3.2 Entry and exit decisions

We assume the firm is rational and maximizes the present-discounted sum of its expected profits. The problem has three state variables: profitability θ_t, experience status $x \in \{i, e\}$, and, conditional on being experienced, the shifter ψ. Henceforth, it will be convenient to work with normalized profitability, defined as $\tilde{\theta}_t \equiv \frac{\kappa\theta_t}{F}$. By Ito's Lemma, $\tilde{\theta}_t$ is a GBM with the same parameters as θ_t.

The firm's problem is to choose an exporting policy $\{y_e(\tilde{\theta};\psi), y_i(\tilde{\theta})\}_{\psi,\tilde{\theta}}$ to maximize profits, where $y_e(\tilde{\theta};\psi)$ and $y_i(\tilde{\theta})$ are indicator variables equal to one if the firm exports and zero otherwise. We solve the problem in two steps. Since $x = e$ is an absorbing state, we first solve for the optimal policy of an experienced firm, $\{y_e^*(\tilde{\theta};\psi)\}_{\psi,\tilde{\theta}}$. We then solve for the optimal policy of an inexperienced firm, $\{y_i^*(\tilde{\theta})\}_{\tilde{\theta}}$, taking into account that once it becomes experienced it follows $\{y_e^*(\tilde{\theta};\psi)\}_{\psi,\tilde{\theta}}$.

The experienced firm In Appendix D.1, we show that the experienced firm's problem can be written as the solution to the following Hamilton-Jacobi-Bellman (HJB) equation,

$$rV_e(\tilde{\theta};\psi)dt = \max_{y\in\{0,1\}} \left\{F\left(\psi\tilde{\theta} - 1\right)y\right\}dt + \mathbb{E}\left(dV_e(\tilde{\theta};\psi)\right). \tag{2}$$

This equation states that the firm's return equals the instantaneous profit flow plus expected capital gains. Since future profitability is independent of the firm's actions and there are no exit or re-entry costs, the exporting decision only depends on whether current profits are non-negative. Thus, the firm's optimal policy is simply $y_e^*(\tilde{\theta};\psi) = 1$ if $\tilde{\theta} \geq \frac{1}{\psi}$ and $y_e^*(\tilde{\theta};\psi) = 0$ if $\tilde{\theta} < \frac{1}{\psi}$.

The inexperienced firm In Appendix D.1, we show that the inexperienced firm's problem can be written as the solution to the following HJB equation,

$$rV_i(\tilde{\theta})dt = \max_{y\in\{0,1\}} \left\{ F\left(\tilde{\theta} - 1\right) + \lambda\left(\mathbb{E}_\psi V_e(\tilde{\theta};\psi) - V_i(\tilde{\theta})\right)\right\} ydt + \mathbb{E}\left(dV_i(\tilde{\theta})\right). \tag{3}$$

The term in brackets in equation (3) highlights the trade-off underlying the firm's exporting decision. By exporting, the firm gains a chance of becoming experienced, and the term $\lambda(\mathbb{E}_\psi V_e(\tilde{\theta};\psi) - V_i(\tilde{\theta}))$ captures this benefit of experimentation. This term is always positive, since profits are higher for an experienced firm. When $\tilde{\theta} \geq 1$, current profits are also non-negative, so inexperienced firms strictly prefer to export. When $\tilde{\theta} < 1$, however, current profits are negative, i.e. $F(\tilde{\theta} - 1) < 0$, and the firm faces a trade-off: it can experiment in the hope of becoming experienced, but only by incurring a contemporaneous loss. The following proposition shows that there exists a region $(\tilde{\theta}^*, 1)$ in which firms choose to experiment.[14]

Proposition 1. *(a) The unique piecewise-continuous optimal policy is characterized by a threshold $\tilde{\theta}^* \in [0,1)$ such that if $\tilde{\theta} < \tilde{\theta}^*$, the firm does not export while if $\tilde{\theta} > \tilde{\theta}^*$, the firm exports; (b) $\tilde{\theta}^*$ solves*

$$F\left(\tilde{\theta}^* - 1\right) + \lambda\left(\mathbb{E}_\psi V_e(\tilde{\theta}^*;\psi) - V_i(\tilde{\theta}^*)\right) = 0. \tag{4}$$

Proof. See Appendix D.2.

In Appendix D.3, we show that equation (4) can be solved to obtain

$$\tilde{\theta}^* - 1 + \lambda\left(\frac{2}{J+\tilde{J}}\right)\left\{\int_{\tilde{\theta}^*}^{\infty}\left(\frac{\tilde{\theta}^*}{z}\right)^{\tilde{\beta}_1}\left(\mathbb{E}_\psi\left(\max\left(\psi z - 1, 0\right)\right) - (z-1)\right)\frac{dz}{z} \right. \\ \left. + \int_0^{\tilde{\theta}^*}\left(\frac{\tilde{\theta}^*}{z}\right)^{\beta_2}\mathbb{E}_\psi\left(\max\left(\psi z - 1, 0\right)\right)\frac{dz}{z}\right\} = 0, \tag{5}$$

where $J = \sqrt{\mu^2 + 2r\sigma^2}$, $\tilde{J} = \sqrt{\mu^2 + 2\left(r+\lambda\right)\sigma^2}$, $\tilde{\beta}_1 = \frac{-\mu+\tilde{J}}{\sigma^2} > 1$ and $\beta_2 = \frac{-\mu-J}{\sigma^2} < 0$.

The intuition for equation (5) is as follows. The solution can be written as an integral of flow profits over states z, weighted by the discounted time the process spends in each state. For states with $z > \tilde{\theta}^*$, the inexperienced firm exports, so the relevant integrand is the difference between the expected flow profits of an experienced and an inexperienced firm, discounted at rate $r + \lambda$. For states with $z < \tilde{\theta}^*$, the inexperienced firm does not export, so the relevant integrand includes only the expected flow profits of an experienced firm, discounted at rate r.

Equation (5) shows a convenient feature of our model: only one equation in one unknown needs to be solved to characterize the firm's strategy.[15] Furthermore, note that F and κ do not appear

[14] Appendix D.2 provides a set of sufficient conditions that guarantee that the firm follows a single-threshold strategy, nesting the GBM-Pareto structure assumed here.

[15] π_i and π_e being both linear in θ (or, equivalently, ψ being multiplicative) is not essential for this result. In Appendix D.3 we show that with general profit functions $\pi_i(\theta)$ and $\pi_e(\theta;\psi)$ the problem can still be reduced to one equation in one unknown.

in equation (5), so $\tilde{\theta}^*$ does not depend on these parameters. Intuitively, firms offset differences in κ and F by timing entry appropriately: for example, a low-κ firm waits longer until θ is large enough to compensate for its lower profitability. This property will be important in the next section and in the empirical exercise.

The left and right panels of Figure 3 plot two sample paths of operating profits normalized by fixed costs (orange solid line). In both panels, the path of time-varying profitability, $\{\tilde{\theta}_t\}_{t=0}^{\infty}$, and the timing of learning conditional on exporting are identical; the only difference is the realization of ψ. Firms are initially inexperienced and remain out of the market while normalized profits lie below $\tilde{\theta}^*$ (blue dashed line). Once $\tilde{\theta}_t$ exceeds $\tilde{\theta}^*$, they begin exporting even though they initially incur losses, because exporting allows them to experiment and resolve uncertainty about ψ. As profitability later declines, firms exit before becoming experienced. When profitability rises again, they re-enter. This is the first type of re-entrant in our model: the inexperienced re-entrant, which is behaviorally identical to a first-time entrant. During this second export spell, firms become experienced, and the relevant threshold falls to 1. In the left panel, the realization of ψ is too low, so the firm exits; in the right panel, it is high enough for the firm to continue exporting. As profitability later declines, even the high-ψ firm eventually exits and later re-enters. This is the second type of re-entrant in our model: the experienced re-entrant.

Understanding survival upon entry for this type of re-entrant, an experienced firm, vis-à-vis a first-time entrant, an inexperienced firm, is the key to explaining Fact 2. We study this next.

3.3 Survival upon entry: Key properties

Henceforth, we assume that all firms are born inactive in the export market, i.e. $\frac{\kappa\bar{\theta}}{F} < \tilde{\theta}^*$. Normalizing entry to $t = 0$, an inexperienced firm enters the foreign market at $\tilde{\theta}_0 = \tilde{\theta}^*$. Since $\tilde{\theta}_t$ follows a GBM,

$$\ln \tilde{\theta}_t = \ln \tilde{\theta}^* + \mu t + \sigma Z_t,$$

where Z_t is distributed $\mathcal{N}(0, t)$. Defining $k_t \equiv \frac{\ln \tilde{\theta}_t - \ln \tilde{\theta}^*}{\sigma}$,

$$k_t = \frac{\mu}{\sigma} t + Z_t.$$

An inexperienced firm is active if and only if

$$\ln \tilde{\theta}_t > \ln \tilde{\theta}^* \Leftrightarrow k_t > 0 \Leftrightarrow Z_t > -\frac{\mu}{\sigma} t. \quad (6)$$

Hence, the probability of being active at time t depends only on $\frac{\mu}{\sigma}$. Intuitively, once the drift is normalized by volatility, the variance of the process affects the scale of the trajectory but not whether it lies above or below the entry threshold. Since an exporter becomes experienced with intensity λ, the likelihood of becoming experienced depends only on $\frac{\mu}{\sigma}$ and λ.

Now define $\tilde{\psi} \equiv \left(\frac{\psi}{\psi_m}\right)^{\frac{1}{\sigma}}$, which is distributed Pareto$(1, \alpha\sigma)$. When a firm is experienced, it is

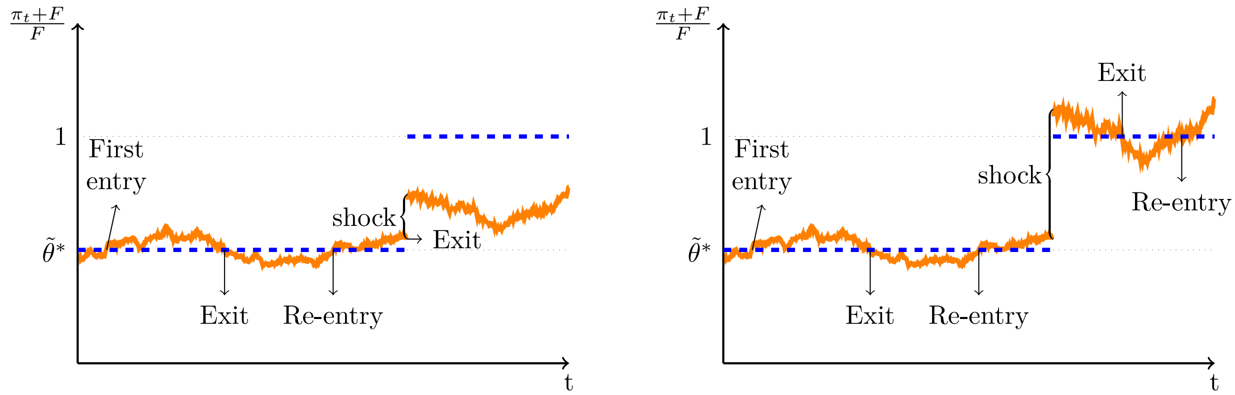


Figure 3: Sample paths

Notes: These figures plot sample paths for gross revenues normalized by fixed costs, i.e. $\frac{\pi+F}{F}$. This corresponds to $\tilde{\theta}_t$ when the firm is inexperienced and $\psi\tilde{\theta}_t$ when the firm is experienced. The left panel plots a case with a low realization of ψ, while the right panel plots a case with a high realization of ψ.

active if and only if

$$\ln\tilde{\theta}_t + \ln\psi > 0 \Leftrightarrow k_t + \ln\tilde{\psi} > -\frac{\ln(\psi_m\tilde{\theta}^*)}{\sigma} \Leftrightarrow Z_t + \ln\tilde{\psi} > -\frac{\mu}{\sigma}t - \frac{\ln(\psi_m\tilde{\theta}^*)}{\sigma}. \tag{7}$$

Hence, the probability of being active depends only on $\frac{\mu}{\sigma}$, $\frac{\ln(\psi_m\tilde{\theta}^*)}{\sigma}$, and $\alpha\sigma$. As before, the relevant objects are the normalized parameters rather than their levels: changing σ has no effect provided the drift, the effective profitability boost required to survive, and the Pareto shape parameter are adjusted accordingly.

Let $y(t)$ be an indicator function equal to 1 if the firm exports at time t. The results above imply that knowing $\Upsilon = \left\{\frac{\mu}{\sigma}, \lambda, \frac{\ln(\psi_m\tilde{\theta}^*)}{\sigma}, \alpha\sigma\right\}$ is sufficient to determine the likelihood of any given trajectory of $\{y(t)\}_{t=0}^{\infty}$ upon entry. Equivalently, any combination of parameters that delivers the same Υ implies the same probability that a firm exports at any given instant. We refer to this aspect of an export trajectory as the "extensive margin" of exporter dynamics.

To contrast the model with the data, we study moments that aggregate events over multiple instants. Among these moments, we define a class, M_1, consisting of moments that aggregate only over the extensive margin. Formally, let $g : \{y(t)\}_{t=0}^{\infty} \to \mathbb{R}$ be a function that maps a given survival trajectory, i.e. a series of zeros and ones, into a number. For example, when we study survival at horizon T, for any trajectory $\{y(t)\}_{t=0}^{\infty}$, the function g returns 1 or 0 depending on whether the firm exports at least once between T and $T+1$. The moment of interest m is then the average of this indicator across firms, i.e. $m = \mathbb{E}g$. In this example, the resulting moment is the model prediction for one point in Figure 2b.

Any moment m in this class, M_1, depends only on Υ, as shown in Proposition 2 below. This is important because these moments are robust to assumptions about other parameters of the problem or unspecified features of the environment, such as the mapping between profitability and sales. The survival-upon-entry moments that constitute Fact 1 and Fact 2 are particular cases, and we use them to discipline the model. In Section 6.1, we study other common survival and re-entry moments in this class.

Proposition 2. *We say that a moment m belongs to a class of moments M_1 if it can be written as $m = \mathbb{E}(g)$ for some function $g : \{y(t)\}_{t=0}^{\infty} \to \mathbb{R}$. Any moment $m \in M_1$ depends only on Υ. In particular, the survival moments that constitute Facts 1 and 2 in Section 2 belong to M_1 and, therefore, depend only on Υ.*

Proof. In the text, we show that the probability of any individual event $y(t) \in \{0, 1\}$ only depends on Υ. We only need to show that the same is true for the argument of g, namely, a trajectory comprised of individual instants. Equations (6) and (7), together with the fact that the firm becomes experienced with intensity λ, imply that the likelihood of a given trajectory $\{y(t)\}_{t=0}^{\infty}$ is determined by $\frac{\mu}{\sigma}$, $\frac{\ln(\psi_m \tilde{\theta}^*)}{\sigma}$, λ, $\tilde{\psi}$, and $\{k_t\}_{t=0}^{\infty}$. Moreover, $\tilde{\psi}$ is distributed Pareto$(1, \alpha\sigma)$. By Itô's Lemma, k_t is a GBM with drift $\frac{\mu}{\sigma}$ and unit variance. Therefore, the likelihood of any given trajectory $\{k_t\}_{t=0}^{\infty}$ depends only on $\frac{\mu}{\sigma}$. This proves the result. □

Proposition 2 also implies the following corollary:

Corollary 1. *Any moment m in class M_1 is independent of κ and F. In particular, as the moments that constitute Facts 1 and 2 in Section 2 belong to M_1, they are independent of κ and F.*

Proof. By Proposition 2, m only depends on Υ. From equation (5) it follows that $\tilde{\theta}^*$ is independent of κ and F. Thus, m is also independent of κ and F. □

Corollary 1 is a key result because it establishes that the survival probability of an export incursion is independent of κ and F, and therefore depends only on parameters common across firms.[16] The main implication is that all firms entering a given market have the same probability of survival T periods after entry. This prediction holds despite substantial heterogeneity in profit shifters (κ) and fixed costs (F) across firms and markets. Heterogeneity in κ affects the likelihood of different entry sequences into foreign markets, but it does not affect survival once entry has occurred.

Since entry profits satisfy $\pi_0 \propto F$ (with common factor of proportionality $\tilde{\theta}^*$), heterogeneity in F also implies heterogeneity in sales at the time of entry. For example, if sales are a constant proportion of profits, entry sales are also proportional to fixed costs. Thus, the model retains enough flexibility to rationalize the shape of the firm size distribution through the distribution of fixed costs. Most results in this paper do not depend on specific assumptions about that distribution, so we do not need to impose them. These implications of Corollary 1 highlight an advantage of focusing

[16] An analogous result concerning heterogeneous market-specific profitability shifters is obtained in Albornoz et al. (2016) in a framework without experimentation.

on entrant survival: we obtain sharp predictions for observables without sacrificing flexibility over firm-specific parameters about which we know little.

We now provide a sharper characterization of the facts described in Section 2. The survival probability upon entry of a first-time entrant at horizon T is given by:[17]

$$p^{ft}(T) = \Pr(\exists t \in (T, T+1) | y(t) = 1, \tilde{\theta}_0 = \tilde{\theta}^*). \tag{8}$$

The survival probability of a re-entrant is defined similarly, except that we must account for whether the firm is experienced at re-entry:

$$\begin{aligned} p^{re}(T) = & \Pr(x_{re} = e) \Pr(\exists t \in (T, T+1) | y(t) = 1, \tilde{\theta}_0 = 1) + \\ & \Pr(x_{re} = i) \Pr(\exists t \in (T, T+1) | y(t) = 1, \tilde{\theta}_0 = \tilde{\theta}^*) \end{aligned} \tag{9}$$

where $\Pr(x_{re} = i)$ and $\Pr(x_{re} = e)$ denote the probabilities that a firm is inexperienced and experienced at the moment of re-entry, respectively. In the special case without experimentation ($\lambda = 0$), there is no difference between the survival probabilities of first-time entrants and re-entrants. With experimentation ($\lambda > 0$), inexperienced and experienced firms behave differently. All first-time entrants are inexperienced, whereas only a fraction of re-entrants are. Their survival probabilities therefore differ. Since λ is the key parameter governing this composition effect, it is crucial for matching the size of the survival gap between first-time entrants and re-entrants.

The other key parameter that helps the model explain Facts 1 and 2 is α, which governs the uncertainty surrounding the firm's future profitability in the export market, ψ. As α decreases, the mean and variance of ψ increase. Because firms can always exit, they are willing to take a gamble in this model: they benefit from a high realization of ψ, but can stop exporting if ψ turns out to be low.[18] Thus, when the variance of the shock is larger, firms have stronger incentives to enter export markets early in the hope that a favorable realization will substantially increase profits. Proposition 3 formalizes this intuition by establishing that the threshold $\tilde{\theta}^*$ increases with α.

Proposition 3. *The normalized threshold $\tilde{\theta}^*$ increases with α.*

Proof. See Appendix D.4. □

Although it is natural to think that earlier entry into the export market should lower survival probabilities, this need not always be the case. A lower α also raises the likelihood of large realizations of ψ, which place the firm well above the exit threshold and make it more likely to survive. For this reason, no general proposition can be obtained about the effect of a lower α on survival.

[17] Previous research often focuses on "instantaneous" survival probabilities, e.g. $\Pr(y(T) > 1)$. We find that, in the context of our paper, these instantaneous measures are useful abstractions to build intuition, but they provide a poor quantitative approximation to the objects we can measure in the data. The reason is that firms spend a good share of their time close to the threshold, and there is an important margin of variation given by the amount of time a firm decides to export within a year. We discuss these time-aggregation issues in Section 6 and Appendix B.

[18] Formally, this risk-loving behavior is captured in equation (5) by the term $\mathbb{E}_\psi(\max\{\psi z - 1\})$, which decreases with α.

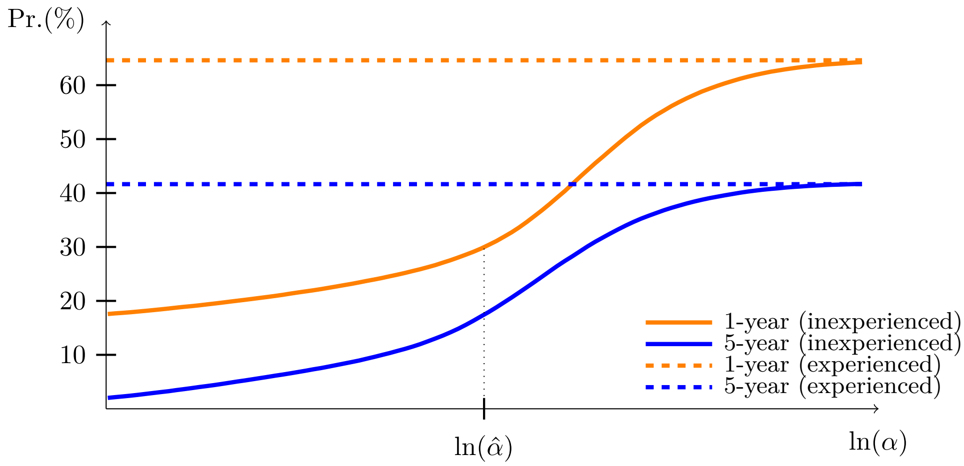


Figure 4: The effect of uncertainty (α)

Notes: The horizontal axis is $\ln(\alpha)$. Solid lines plot survival probabilities of an inexperienced first-time entrant at one-year (orange) and five-year (blue) horizons as α varies, with the remaining parameters at their estimated values. Dashed lines show the corresponding survival probabilities for an experienced firm (i.e. the $\lambda = 0$ benchmark). The vertical dotted line marks $\ln(\hat{\alpha})$.

Nevertheless, at our estimated parameter values, firms experiment aggressively, so the intuitive result holds: inexperienced firms' survival probability is lower than that of experienced firms at all horizons, and the gap between them increases with uncertainty. This implication of a lower α is shown in Figure 4, which plots the survival probability of an inexperienced first-time entrant (solid lines) as a function of α at one-year and five-year horizons, with the remaining parameters at their estimated values. Note that, as $\alpha \to \infty$, the gains from experimentation vanish and the model's predictions converge to the survival rates of experienced firms (dashed lines).

One may wonder to what extent these results are driven by uncertainty, since α also changes the mean of the distribution. A clean way to address this concern is to vary the scale parameter ψ_m, which changes the mean of the distribution while keeping its shape fixed. Proposition 4 shows that a more attractive distribution, i.e. one with a higher ψ_m, leads firms to survive more, not less.

Proposition 4. *The probability of survival of a first-time entrant at any horizon increases with* ψ_m.[19]

Proof. See Appendix D.5. □

To understand this result, it is useful to compare changes of the same size in ψ_m and κ. Recall that the normalized threshold $\tilde{\theta}^* = \frac{\kappa\theta^*}{F}$ is independent of κ, which implies that if κ increases, then the threshold θ^* decreases exactly enough to keep $\kappa\theta^*$ constant. An increase in ψ_m raises profits for any realization of the shock, just as an increase in κ does. The key difference is that ψ_m does not raise profits during the experimentation period. As a result, relative to an equivalent change in

[19] This is valid for any family of distributions linked by a scale parameter, i.e. if we have two distributions ψ_1, ψ_2 such that $\psi_1 = \psi_m\psi_2$, then the result carries over.

κ, an increase in ψ_m makes the experimentation phase more costly, implying that $\psi_m \tilde{\theta}^*$ increases with ψ_m. In other words, the firm does not fully offset the higher future profits by entering earlier. Hence, once ψ is realized, the inexperienced firm lies farther above the threshold and is therefore more likely to survive.

Proposition 4 is also useful for understanding why uncertainty about ψ is needed to generate lower survival. Consider a firm that knew its ψ in advance. In our model, this would amount to setting $\psi_m = \psi$ and letting $\alpha \to \infty$, so that the jump size becomes deterministic. We know that if $\psi_m = 1$, being experienced is the same as being inexperienced. Therefore, by Proposition 4, if $\psi_m > 1$, this firm would survive less on average as an experienced firm than as an inexperienced firm. Since $\psi \geq 1$ for all firms, a model in which ψ is known ex ante would therefore be unable to explain Fact 2.

In sum, a model with an experimentation phase subject to uncertainty can explain Facts 1 and 2. High uncertainty (i.e., a low α) induces inexperienced firms to experiment aggressively, which explains high early exit rates. Moreover, because the model can generate low short-horizon survival rates without relying on a negative trend, it retains enough flexibility in $\frac{\mu}{\sigma}$ to match the flat survival profile in Fact 1. Finally, Fact 2 arises from a composition effect: first-time entrants are 100% inexperienced, whereas only a fraction of re-entrants are. The remaining experienced re-entrants do not engage in risky experimentation and therefore survive more.

4 Estimation

We discipline the model parameters using the moments underlying Facts 1 and 2 in Section 2. An immediate implication of Proposition 2 is that our model has only four degrees of freedom to match these moments. That is, any combination of parameters $\{\mu, \sigma, \lambda, \alpha, \psi_m, r\}$ that yields the same $\Upsilon = \{\frac{\ln(\psi_m \tilde{\theta}^*)}{\sigma}, \frac{\mu}{\sigma}, \sigma\alpha, \lambda\}$ will imply the same extensive-margin moments.[20] To make progress, we set $r = 0.1$ and make the natural assumption that $\psi_m = 1$, which implies that the firm learns nothing under the worst possible realization of ψ. This value for ψ_m also has the appealing property of converging to a standard model without experimentation as uncertainty decreases, i.e. as $\alpha \to \infty$. We are thus left with $\varphi = \{\mu, \sigma, \lambda, \alpha\}$, which we estimate via simulated method of moments (SMM). Our SMM estimator chooses φ to minimize $m(\varphi)' m(\varphi)$, where $m(\varphi)$ are the ten survival moments in Section 2 (details in Appendix E).

4.1 Results

The top part of Table 2 displays the estimation results. The parameters of the GBM are $\hat{\mu} = -0.010$ and $\hat{\sigma} = 0.043$. These values imply that the normalized drift of the GBM is $\frac{\hat{\mu}}{\hat{\sigma}} = -0.230$, which is somewhat smaller than the method-of-moments estimates of -0.279 and -0.270 obtained by Luttmer (2007) and Arkolakis (2016), respectively, for this ratio. Under the light of our model, a

[20] Note that the normalized threshold $\tilde{\theta}^*$ is a function of these six parameters; see equation (5).

Table 2: SMM Estimation results

	Fixed parameters	
r	0.1	
ψ_m	1	
	Estimated parameters	
μ	-0.010	
σ	0.043	
λ	3.150	
α	9.742	
	Survival probabilities	
	Panel A: First-time entrants	
	Model	Data
Year 1	0.300	0.294
Year 2	0.220	0.242
Year 3	0.195	0.208
Year 4	0.182	0.185
Year 5	0.174	0.169
	Panel B: Re-entrants	
Year 1	0.442	0.405
Year 2	0.356	0.357
Year 3	0.317	0.329
Year 4	0.293	0.290
Year 5	0.274	0.282

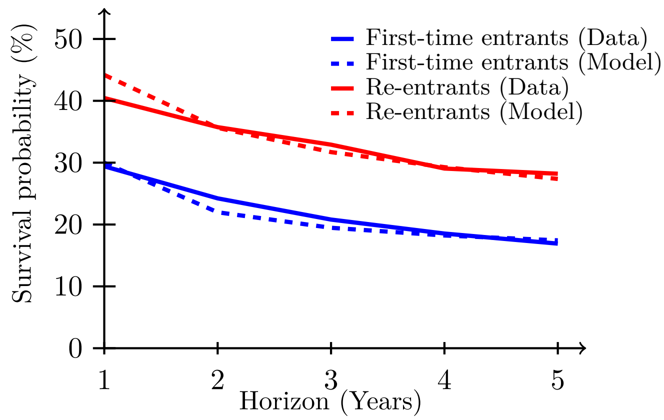


Figure 5: Survival profiles predicted by the model

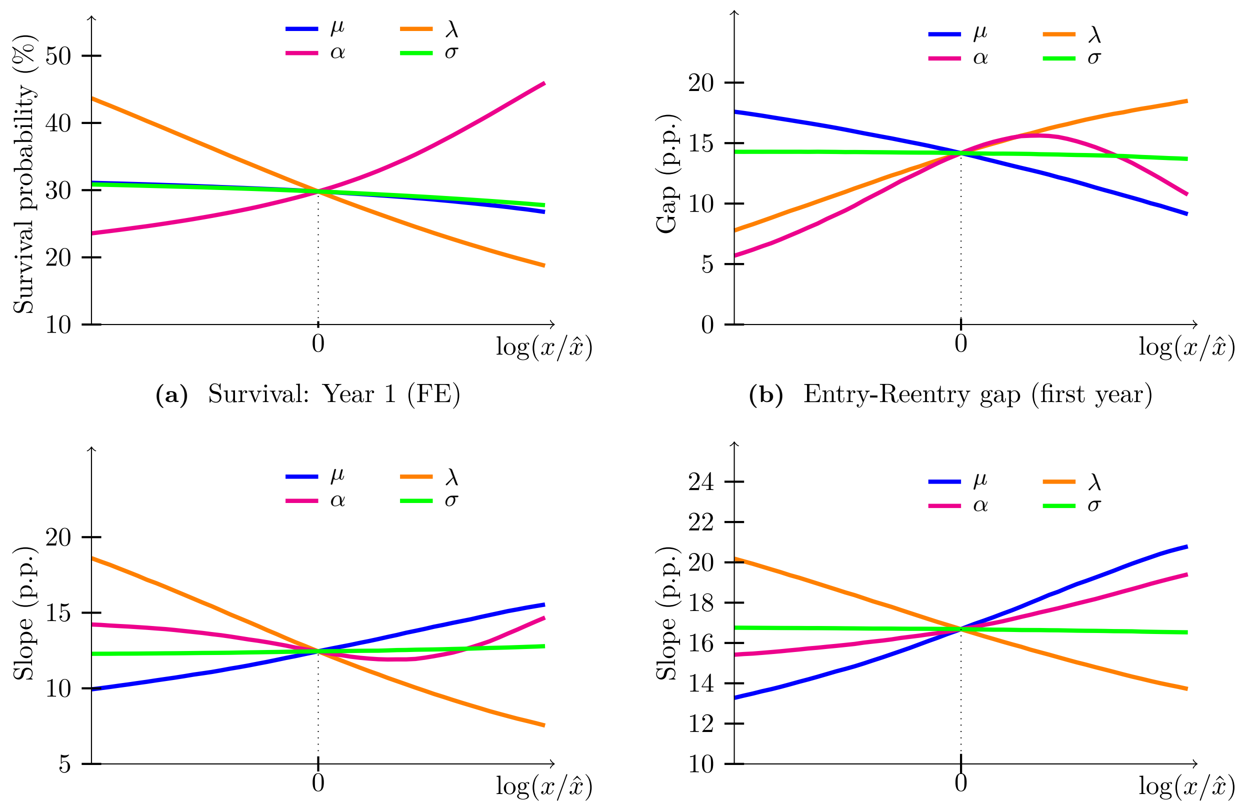
normalized drift $\frac{\mu}{\sigma}$ closer to zero is required to explain the "flatness" of the survival profile, especially for re-entrants, who are more sensitive to the GBM drift, as they include experienced firms. The low survival rates are explained instead by the experimentation mechanism, which is governed by α and λ.[21] The estimate for the parameter of the Poisson process is $\widehat{\lambda} = 3.15$. This estimate implies that a firm that continuously exports has a 23.1% probability of becoming experienced within a month. The Pareto shape parameter is $\widehat{\alpha} = 9.74$. To put this estimate into perspective, note that $\alpha\sigma$ is the sufficient statistic governing uncertainty in the normalized model (Proposition 2). The standard deviation of the log Pareto shock is $1/\alpha$, so the ratio of the permanent shock's volatility to the annual volatility of the Brownian motion is $1/(\alpha\sigma)$. At our estimates, $\widehat{\alpha}\widehat{\sigma} = 0.42$, implying that the one-time permanent shock from becoming experienced has a standard deviation about 2.4 times the annual volatility of the GBM. Furthermore, the estimates imply that only about 41% of re-entrants are experienced. Having a substantial share of inexperienced firms among re-entrants is necessary to explain that even re-entrants have a low and flat survival profile.

The second part of Table 2 compares the data with the model predictions. Figure 5 provides a visual representation of the same information. The model does an excellent job. In particular, it predicts a low and flat survival profile for both first-time entrants and re-entrants and an average gap of about 12 percentage points between both, as in the data. The average absolute discrepancy between data and predictions is slightly above a percentage point, with the largest discrepancy in the first year for re-entrants (44.2% in the model versus 40.5% in the data).

4.2 Parameter identification

The four structural parameters affect all ten moments, so providing intuition for the individual identification of each is not straightforward. Proposition 2 provides guidance: survival moments depend on the parameters only through Υ. Holding σ constant, μ, λ, and α each map into one

[21]Indeed, in Section 4.3 we show that, in the absence of experimentation, $\frac{\mu}{\sigma}$ needs to be three times as large to match the low survival rates of exporters.



(a) Survival: Year 1 (FE)

(b) Entry-Reentry gap (first year)

(c) Survival: Year 1 vs Year 5 (FE)

(d) Survival: Year 1 vs Year 5 (RE)

Figure 6: Parameter identification

Notes: Each panel plots the indicated moment as a function of $\log(x/\hat{x})$, where x is varied from 0.5 to 2 times its estimated value. The four lines vary one structural parameter at a time: μ (blue, with σ, λ, α fixed), λ (orange, with μ, σ, α fixed), α (magenta, with μ, σ, λ fixed), and σ (green, adjusting μ and α to hold μ/σ, $\alpha\sigma$, and λ fixed). Note that $\hat{\mu} < 0$, so a more negative μ corresponds to moving right. The vertical axes are: (a) first-year survival probability of a first-time entrant; (b) first-year re-entrant minus first-time entrant survival probability; (c) first-year minus fifth-year survival rates of a first-time entrant; (d) first-year minus fifth-year survival rates of a re-entrant.

of the three exogenous elements of Υ: μ/σ, λ, and $\alpha\sigma$, respectively. In Figure 6, we vary each of these three parameters from 0.5 to 2 times its estimated value, holding the remaining structural parameters fixed. As a fourth experiment, we vary σ while adjusting μ and α to hold μ/σ, $\alpha\sigma$, and λ fixed, so that no exogenous element of Υ changes. Since survival moments depend only on Υ, any effect of σ in this experiment can come only through the endogenous element, $\ln(\psi_m\tilde{\theta}^*)/\sigma$.

Consider first the main feature of Fact 1: the high exit rate early upon entry. Figure 6a plots the first-year survival probability of a first-time entrant as we vary each parameter from 0.5 to 2 times its estimated value. A higher λ increases the speed of the potential prize, making firms experiment more aggressively and thus survive less. A lower α increases the magnitude of the potential prize and lowers the entry threshold (Proposition 3), also reducing survival. These two parameters dominate this moment: λ and α each generate over 20 percentage points of variation, while μ generates less than 5. Regarding μ, a more negative value implies a more negative normalized drift μ/σ, which leads, as in the benchmark model, to lower survival rates.[22]

Second, consider Fact 2, i.e. the gap between the survival profile of first-time entrants and re-entrants. Since re-entrants survive more than first-time entrants, the experimentation mechanism must be active, i.e. $\lambda > 0$ and $\alpha < \infty$. Figure 6b plots the first-year survival-rate gap between first-time entrants and re-entrants, also varying one parameter at a time. The effect of λ is straightforward: (i) it lowers survival among first-time entrants by making them more eager to enter and, (ii), it increases re-entrant survival relative to first-time entrants since firms are more likely to be experienced when they re-enter. Both effects increase the gap. By contrast, the effect of α is more subtle. On the one hand, as discussed in Section 3.3, a lower α (higher uncertainty) lowers the entry threshold (Proposition 3), decreasing survival among inexperienced firms and thus increasing the gap. However, α also affects the composition of re-entrants. When α is low, firms bet on a small probability yet very profitable outcome. As most firms receive negative news (i.e. an insufficient ψ) and are very unlikely to re-enter, there are few experienced re-entrants. Thus, in this case, most re-entrants are inexperienced, which reduces the gap. In our simulations, the effect of α on the gap is hump-shaped: the composition effect dominates at low α, while the gap also declines at high α as the experimentation mechanism fades.[23] Finally, a more negative μ/σ reduces the gap through two channels: it lowers the fraction of experienced re-entrants, as firms exit sooner with less time to receive the shock, and it compresses the survival advantage of experience.

Finally, consider the second key feature of Fact 1: flat survival profiles. To capture this feature, Figures 6c and 6d plot the difference between first- and fifth-year survival rates among first-time entrants and re-entrants, respectively. A larger λ makes the profile flatter by killing more firms early, leaving survivors who have largely resolved their uncertainty. By contrast, a more negative μ/σ makes the profile steeper, as the negative drift compounds over longer horizons. The effect of μ/σ is larger for re-entrants (panel d), who are less affected by the experimentation shock. The effect of α depends on both the location in the parameter space and the horizon: it is non-monotone and small for first-time entrants (panel c), but monotonically increasing and more sizeable for re-entrants (panel d). This difference in behavior across panels contributes to the separate identification of μ/σ and $\alpha\sigma$.

Across all four panels, varying σ while holding μ/σ, $\alpha\sigma$, and λ fixed (green line) has a negligible effect. Proposition 2 clarifies why: since survival moments depend on σ only through Υ, the only channel is the endogenous element $\ln(\psi_m\tilde{\theta}^*)/\sigma$. Quantitatively, this channel turns out to be weak in this region of the parameter space. Thus, survival moments sharply identify λ, μ/σ, and $\alpha\sigma$, but are largely uninformative about the level of (μ, σ, α).

Table 3: SMM estimation results
(Benchmark model)

	Estimated parameter	
μ/σ	-0.71	
	Survival probabilities: First-time entrants	
	Model	Data
Year 1	0.416	0.294
Year 2	0.265	0.242
Year 3	0.181	0.208
Year 4	0.128	0.185
Year 5	0.091	0.169

4.3 Benchmark and sunk-cost models

In this section, we shut down experimentation ($\lambda = 0$). We first show where this "benchmark" model fails, then ask whether sunk costs—the traditional source of history dependence in the exporter dynamics literature (e.g. Baldwin and Krugman, 1989; Dixit, 1989; Roberts and Tybout, 1997; Das et al., 2007)—can improve upon the benchmark.

Benchmark model The shortcomings of this model are apparent. Since firms' decisions do not depend on their export history in this benchmark, export history has no impact on survival probabilities, so the model cannot explain Fact 2. More interestingly, the benchmark model is also unable to explain Fact 1. The green-dotted line in Figure 2a (discussed in Section 2) corresponds to the best prediction of the benchmark model. This prediction is obtained by estimating the model with the SMM using only the survival profile of first-time entrants $\{S_t\}_{t=1,\ldots,5}$.[24] In this case, the only object to estimate is the ratio $\widetilde{\mu} = \frac{\mu}{\sigma}$. Table 3 shows that the estimate of this parameter ($\widehat{\widetilde{\mu}} = -0.71$) is much more negative than the one obtained in the full model. The table also presents predicted survival rates, depicted in Figure 2a. We can see that the model overpredicts survival rates at short horizons while underpredicting them at longer horizons.

Sunk costs We augment the benchmark with sunk costs: firms pay S^i upon first entry and $S^e \leq S^i$ upon re-entry.[25] Allowing for positive sunk costs does not improve the benchmark model's ability to explain Fact 1. Figure 7a shows how the survival profile changes when we add a positive sunk cost, holding μ at its benchmark estimate.[26] The larger the sunk cost, the more conservatively

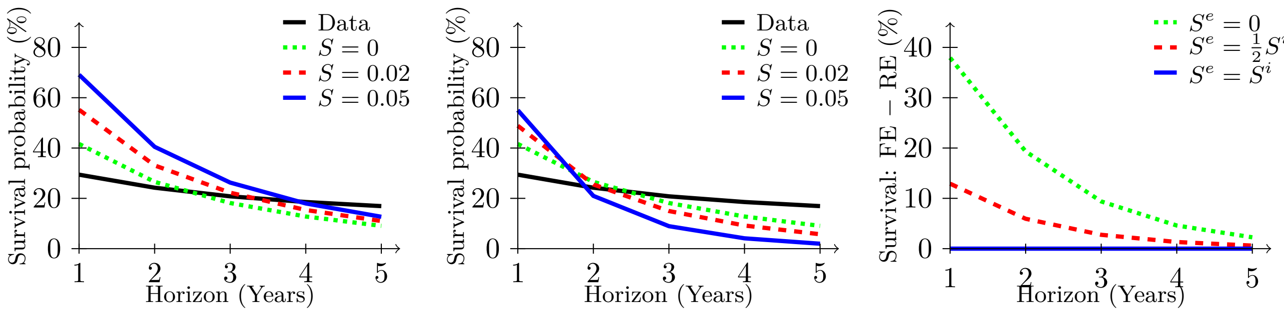
[22] The fact that this effect dominates is a non-trivial numerical result since μ/σ also affects the threshold $\tilde{\theta}^*$.

[23] The gap tends to zero not only when $\alpha \to \infty$ (no uncertainty), but also when uncertainty becomes very large, more precisely when $\alpha \to 1$ from above.

[24] We could alternatively use the ten survival moments, five for first-time entrants and five for re-entrants, to estimate but prefer to focus only on the first five to give the benchmark model more flexibility to fit Fact 1.

[25] See Appendix F for details and derivations.

[26] For this figure, we assume $S^e = S^i$, which provides the best fit for Fact 2.



(a) Varying S **(b)** Varying S, μ re-estimated **(c)** Entry-Reentry gap varying S^e

Figure 7: The effect of sunk costs on survival probabilities

Notes: In all panels, experimentation is shut down ($\lambda = 0$) and σ is normalized to 0.1. Sunk costs are set exogenously at the values indicated. $S = 0.02$ means the sunk cost is 2% of the annual fixed cost. Panel (a): μ is fixed at its benchmark estimate (-0.071); survival profiles are plotted for $S = S^e = S^i \in \{0, 0.02, 0.05\}$. Panel (b): μ is re-estimated via SMM to fit Fact 1 for each value of S ($\hat{\mu} = -0.086$ for $S = 0.02$; $\hat{\mu} = -0.112$ for $S = 0.05$). Panel (c): $S^i = 0.05$ with μ at the corresponding re-estimated value (-0.112); the re-entrant sunk cost S^e is varied. The panel plots the difference in survival between first-time entrants and re-entrants.

firms enter to improve their odds of recovering the initial losses, and thus, the larger the difference between their entry and exit thresholds. Hence, they survive more. In fact, firms survive more especially in early periods, when the implications of their conservative entry, i.e. still being far from the exit threshold, gain prominence to explain survival relative to the natural drift and volatility of the profitability process. However, this is the opposite of what was needed to improve the benchmark model's fit to Fact 1: flattening the survival profile. Indeed, Figure 7b shows that the survival profile becomes steeper when we re-estimate the drift μ, as the model needs an even more negative drift to counter the higher survival.

The implications of introducing sunk costs are even more at odds with the fact that re-entrants survive more than first-time entrants (Fact 2). Figure 7c plots the difference between the survival profile of first-time entrants and re-entrants, with μ at its re-estimated value and $S^i = 0.05$, under two alternative assumptions on the re-entry cost: half repayment and free re-entry (notice that in the full repayment case maintained so far, this difference is zero). As re-entrants face lower sunk costs, they enter less conservatively and thus survive less. This is the opposite of what is needed to explain Fact 2.

4.4 Infra-marginal entry

The analytical results in Section 3 rely on the assumption that all export entrants and exiters are marginal, i.e. they enter and exit when they smoothly cross a profitability threshold. This assumption is natural at the firm–destination level of our empirical analysis, where the relevant state variable plausibly evolves smoothly. However, it may not hold in two empirically relevant cases: (i) "born-global" firms that enter infra-marginally with productivity far above the export threshold;

and (ii) export entries triggered by large jumps in profitability, such as trade liberalizations or sharp exchange-rate movements.

Born-global firms enter far above θ^* and therefore survive at higher rates than marginal entrants. At the same time, conditional on exit, they are also more likely to be experienced and thus to re-enter as experienced re-entrants. As a result, their effect on Fact 2 is a priori ambiguous. To study this possibility, Appendix G extends the model to allow for infra-marginal initial profitability. Holding the remaining parameters at their baseline estimated values, we calibrate the additional parameters to match plausible values for the share of firms that ever export and for the share of ever-exporters that are born-global. Table G.1 reports one-year survival rates. The effect on the survival gap depends on the prevalence of born-global firms: when their share is 10%, the gap rises slightly, whereas when it is 25%, the gap declines. In all cases, however, the gap remains large and still requires experimentation to account for it. Absent experimentation, re-entrants have no experience advantage, so born-globals only raise the survival of first-time entrants. As a result, any positive share of born-global firms would overturn Fact 2.

Jumps in profitability can also generate non-marginal entry. Small shocks only activate firms close to the threshold, so their entry remains approximately marginal. Large shocks, however, bring in firms farther from the threshold, making the composition of entrants depend on the shape of their distribution. If the initial distribution differs sufficiently from the steady-state distribution, differences between first-time entrants and re-entrants may arise even in the absence of experimentation (or other dynamic force). Figure G.1 in Appendix G plots these distributions in the baseline and benchmark models. Table G.2 reports survival rates following unexpected permanent increases in profitability of 5% and 1% (for reference, the estimated annual standard deviation of profitability is $\sigma = 4.3\%$). In the benchmark model, this composition effect generates only small differences between first-time entrants and re-entrants. In the baseline model, by contrast, the re-entrant survival advantage remains sizable for both shock magnitudes. Thus, even in the presence of large jumps in profitability, experimentation remains the primary driver of the survival gap between first-time entrants and re-entrants.

4.5 Discussion

Our model is not the first to highlight the limitations of the canonical sunk cost model in explaining new exporter dynamics (see e.g. Albornoz et al. (2016); Ruhl and Willis (2017); among others). The literature has proposed several extensions to address those limitations, but a consensus on the minimal ingredients an exporter-dynamics model should have has not emerged. Can our results help discriminate among the alternatives?

A general difficulty is that much of this work builds complex structural models whose predictions about our facts are hard to guess without full model estimation—beyond the scope of this paper. In contrast, our framework is deliberately stylized to make the mapping from assumptions to results transparent. As such, a key advantage is that it sheds light on which model ingredients matter for the facts we study, and which do not.

A first lesson from our framework is that deterministic features that improve firm performance during the first export spell, such as the renowned "learning by exporting" idea, tend to push against Fact 2. Examples include models in which re-entry is cheaper than initial entry, or in which experienced exporters enjoy higher per-period profits (e.g., Timoshenko (2015a) and Alessandria et al. (2021b)). In such environments, an inexperienced firm has a stronger incentive to remain in the market—and thus tend to survive longer—to become experienced. Although experienced firms are "better", they offset this advantage by re-entering with a lower state of the dynamic profitability process. As a result, the survival probability of re-entrants is lower—the opposite of Fact 2.

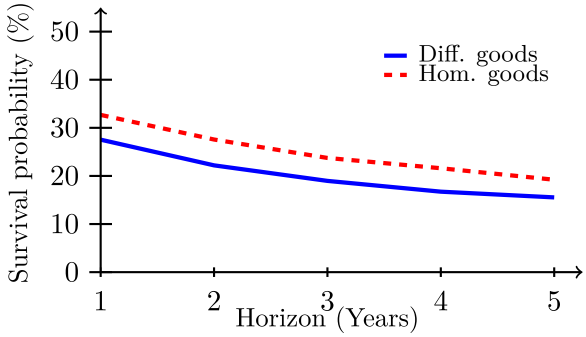
A second lesson from our framework is that ingredients that make the first export spell more volatile can potentially explain the facts by increasing early exit, pushing down the survival rate of first entry relative to subsequent re-entries. Beyond our experimentation-based mechanism, another way to obtain this pattern would be to combine learning in the spirit of Jovanovic (1982), which reduces uncertainty as firms gain experience, with a profitability process volatile enough to produce both exit and re-entry. In this sense, we conjecture that models such as Berman et al. (2019) and Eaton et al. (2025) can reproduce our patterns, at least qualitatively, as would also do an open economy version of Arkolakis et al. (2018). Importantly, uncertainty does not necessarily have to be about product appeal: analogous dynamics would arise if new exporters faced contracting frictions (poorer information about buyer types, e.g. default risk, as in Araujo et al. (2016)) or financial frictions that force them onto more volatile funding.[27] Our model captures these possibilities in a reduced form but is agnostic about the precise micro mechanism behind the higher volatility.

Finally, models in which firms accumulate assets, such as financial wealth (e.g. Kohn et al. (2016)) or customer capital (e.g. Fitzgerald et al. (2024)), can potentially generate composition effects between first-time entrants and re-entrants, yielding survival differences. However, better finance or a larger customer base at entry does not necessarily imply higher survival once endogenous timing is accounted for: e.g. better-capitalized firms optimally enter earlier (at a lower realization of profitability), which can offset the direct advantage of the higher stock. The net effect is therefore subtle and likely dependent on parameter values, whereas the survival gap between first-time entrants and re-entrants in the data is quantitatively substantial—and robust across countries. In this sense, an advantage of our model is that it explains this gap as a natural qualitative prediction.

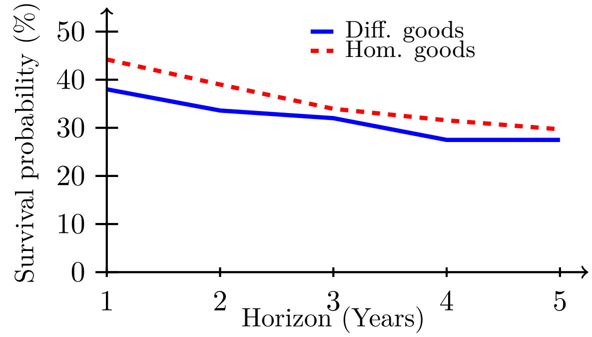
5 Mechanisms

In this section, we provide further evidence on the relevance of uncertainty and experimentation by exploiting variation across products and destinations. A natural interpretation is that firms face greater uncertainty in markets where it is harder to anticipate demand idiosyncrasies, identify

[27] However, exporters may endogenously choose payment terms that reduce default exposure, such as cash-in-advance, in ex-ante riskier destinations so the net effect on volatility is a priori ambiguous; see Schmidt-Eisenlohr (2013) and Antras and Foley (2015).



(a) First-time entrants



(b) Re-entrants

Figure 8: Survival profile by type of product

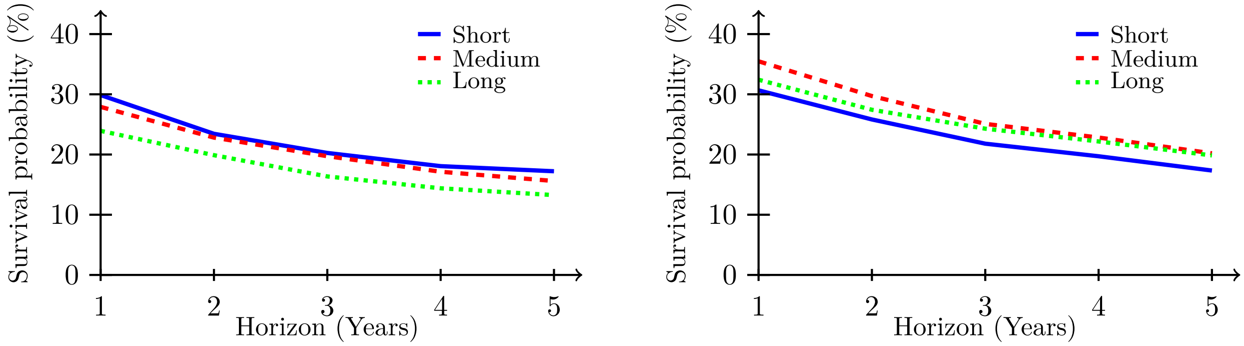
the right distributors, or navigate differences in business culture, which is plausibly the case for differentiated products and more distant destinations. If so, then allowing only α to vary across market groups should already go a long way toward fitting the corresponding survival profiles, with lower estimated values of α in the more uncertain groups.

To test this implication, we classify all incursions in our database in either of two categories, differentiated or homogeneous, following Rauch (1999).[28] We first map export data classified at the Harmonized System 10-digit level into Rev.2 SITC 4-digit categories using the United Nations Statistics Division Conversion Tables. Then, we map the latter categories into one of our two categories.[29] Finally, we identify the category with the largest value of exports in the year of entry and assign the incursion to that category. There are $14,553$ differentiated incursions and $9,701$ homogeneous incursions in our database. Figure 8a displays the survival profile for each category. Consistent with the hypothesis that α is lower for differentiated products, first-time entrants in these products display uniformly lower survival rates. Specifically, the survival rate is more than six percentage points lower in the first year after entry and more than four percentage points lower in the fifth year. The same logic extends to re-entrants: although many have already learned the realization of ψ, a fraction still behaves like first-time entrants and therefore remains exposed to similar early-exit risk. Consistent with this prediction, Figure 8b shows that re-entrants in differentiated products also display uniformly lower survival than re-entrants in homogeneous products. Table A.2 confirms both patterns and shows that they are robust to controlling for composition through destination-year fixed effects.

To assess how survival varies with distance, we divide export destinations into three groups according to their distance from Peru. Short-distance destinations are those with a distance smaller than $3,350$ km. Medium-distance destinations are those with a distance between $3,350$ km and

[28] We merge homogeneous and referenced-priced categories in Rauch (1999) into only one "homogeneous" category.

[29] The mapping from SITC to Rauch leaves 5.82% of the incursions unclassified. We reduce this proportion to 2.61% by assigning to unclassified SITC 4-digit categories the classification of similar SITC 4-digit categories. Of the remaining unclassified instances, 52.47% are transactions without a reported HS code.



(a) Differentiated goods

(b) Homogeneous goods

Figure 9: Survival profile by distance (First-time entrants)

$10,040$ km. Long-distance destinations are those with a distance above $10,040$ km. The cut-offs are chosen so that each distance group has an equal number of incursions. Figure 9a displays the survival profile for each distance group in the case of differentiated goods. The profile is uniformly lower the farther away the destination is. Specifically, one year after entry, the survival rate for the long-distance group is six percentage points lower than for the short-distance group, while five years after entry the gap is four percentage points. Figure 9b displays analogous information for homogeneous products. In that case, we do not see a clear negative relationship between distance and survival. Rather, the pattern is non-monotonic. These patterns are also borne out in the regression results reported in Table A.3, which uses distance as a continuous variable.

Table 4 summarizes the corresponding market-specific estimates when we re-estimate only α group by group, holding μ, σ, and λ fixed at their baseline values. The estimates line up closely with the reduced-form evidence: $\hat{\alpha}$ is lower for differentiated products than for homogeneous products and, within differentiated products, declines with distance. We also report the ratio of the standard deviation of the one-time permanent shock from becoming experienced to the annual volatility of the GBM. The pattern is intuitive: it rises from 2.4 in the baseline to 2.6 for differentiated products as a whole and to 2.9 for differentiated long-distance markets, while it falls to 1.9 for homogeneous medium-distance markets. At the same time, allowing only α to vary already delivers a very good fit to the group-specific survival profiles. The average absolute discrepancy is around one percentage point for first-time entrants in most groups and remains small for re-entrants as well. Appendix H.2 reports the associated model-fit figures for each group.

6 Other relevant exporter dynamics moments

While we have focused so far on Facts 1 and 2, a specific collection of survival moments, the literature has highlighted many other relevant moments that characterize exporter behavior. This section studies our model's ability to explain those other moments. We organize them into three

Table 4: Estimated uncertainty by market group

	Baseline	Diff.	Hom.	Short	Medium	Long	Diff.-Short	Diff.-Medium	Diff.-Long	Hom.-Short	Hom.-Medium	Hom.-Long
$\hat{\alpha}$	9.742	9.038	11.073	10.380	9.731	9.249	10.097	8.751	8.016	11.124	12.313	10.573
Std. dev. ratio	2.4	2.6	2.1	2.2	2.4	2.5	2.3	2.6	2.9	2.1	1.9	2.2
Avg. |p.p.| diff. (FE)	1.0	0.9	1.4	0.8	1.4	1.4	0.7	1.2	1.3	1.4	1.4	2.3
Avg. |p.p.| diff. (RE)	1.2	1.7	1.0	3.1	1.5	1.0	3.7	1.7	1.1	2.1	0.8	2.0

classes. The first class includes additional moments related to exporter survival and re-entry. The second class comprises moments related to export growth. The third class contains moments on survival and growth conditional on size. For each of these classes, we assess (a) the model's ability to explain the moments and (b) the additional assumptions, if any, required to make predictions about them.

6.1 Survival and re-entry moments

Although our model was designed to explain Facts 1 and 2, Proposition 2 implies that it should also be able to predict any moment that belongs to class M_1, which includes all those that aggregate over subsets of the "extensive margin" of exporter behavior (see the discussion in Section 3.3). Many survival and re-entry moments used in the literature belong to this class. Thus, to the extent the model's ability to match our facts stems from a more profound ability to explain the entire extensive margin, it should also match those other moments.

A common practice in the literature is to define "continuous survival" measures based on uninterrupted export experiences (e.g. Eaton et al. (2008) and Ruhl and Willis (2017), among others). For example, a firm that exports to a market for the first time at $t = 0$, does not export at $t = 1$, and exports again at $t = 2$ is not considered a survivor at $t = 2$ under this alternative definition while it is a survivor under the definition used in this paper. Figure 10a computes continuous survival probabilities (i.e. imposing the additional requirement of uninterrupted export spells) in the model (red-dashed line) and in the data (blue-solid line). The model does an excellent job matching these moments, with an average discrepancy of one percentage point. Figure 10b similarly compares "conditional survival" probabilities, which capture the probability of surviving at t conditional on continuous survival until $t - 1$ (i.e. the complement of the hazard rate). Although conditional survival is just a function of continuous survival, which is matched quite accurately, the discrepancies are larger as this measure involves divisions by small numbers.[30]

Pervasive re-entry in export markets is a crucial feature of exporter dynamics. Like survival, re-entry is entirely determined by the extensive margin. That is, once we know the export status of a firm's incursion along its trajectory, we also know the probability of re-entering the market over any period after exit. We compute two re-entry moments. First, Figure 10c plots the share of firms that ever re-enter up to year $t_X + T$, where t_X is the time of the first exit (note $T \geq 2$ by definition

[30]In Appendix H.1, we provide an alternative estimation of the model that adds these conditional survival moments to the estimation strategy. The model's ability to explain these moments improves considerably at the expense of slightly worsening the fit for the re-entrant survival profile (from a 1.2 percentage point average deviation to 2.7).

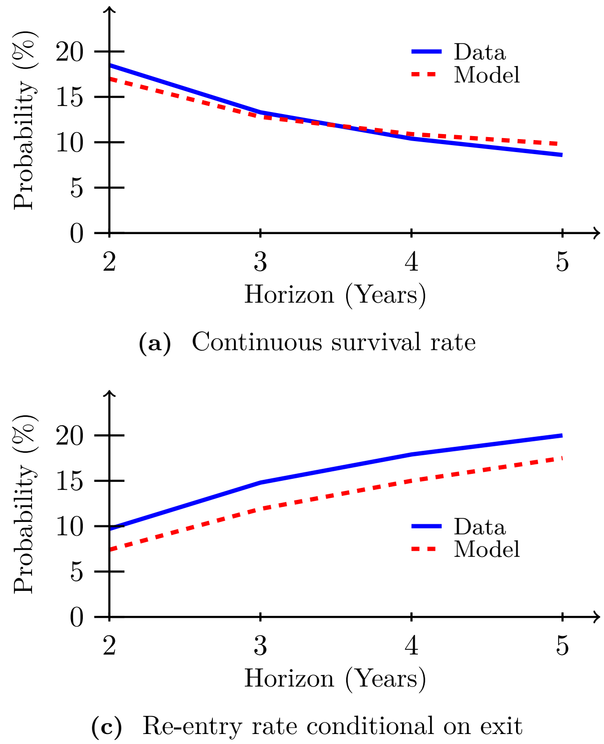


Figure 10: Other moments: Extensive margin

of exit). In the data (blue-solid line), about 10% of exiters have re-entered the market within two years, with that number increasing to 20% within five years. The model (red-dashed line) aligns closely with these numbers. It slightly underestimates the extent of re-entry by two percentage points, primarily due to insufficient early re-entry. Second, Figure 10d plots the probability of exporting in period $t_X + T$. In the data (blue-solid line), the share of exiters at t_X that export in any of the next five years hovers around 9%. The model (red-dashed line) also matches this feature of the data well, with the main discrepancy for $T = 2$, where, by definition, this share coincides with the previous re-entry measure.

Taken together, these facts suggest that despite the parsimony of the model, it does a very good job explaining an important class of moments related to survival and re-entry, which only depend on the extensive margin of exporter behavior.[31]

6.2 Export growth moments

Another class of moments (M_2) studied in the exporter dynamics literature concerns growth in export sales. Unlike extensive-margin moments, predictions on export growth require mapping

[31] One caveat is that the literature typically focuses on annual data based on calendar years instead of defining firm-market-specific years as we do here. In Appendix B.2, we show the results using this alternate way of aggregating shipments. They are similar, except that (both in the model and the data) survival rates are larger because of time-aggregation issues, especially in the first year.

profitability (θ) into sales. Under CES demand, interpreting θ as productivity or quality (see footnote 12), sales are proportional to θ. Annual sales are then, up to a multiplicative constant, $\int_T^{T+1} \theta(t) \cdot \mathbf{1}\{\theta(t) > \theta^*\}\, dt$, and growth rates are defined as log-differences of this integral across consecutive years. This requires no parameters beyond the baseline estimates. More sophisticated models may imply a richer mapping between profitability and sales and, thus, a better ability to explain export growth moments. However, our purpose here is to assess how far this restricted version of the model can go in explaining the moments in M_2.

Figures 11a, 11b, and 11c plot the mean, median, and standard deviation of sales growth rates for firms surviving both at $t_0 + T$ and $t_0 + T - 1$.[32] The literature typically expects larger growth rates in early years because of selection: we only observe growth for survivors—firms more likely to have positive growth. Here, however, a countervailing "exiting partial-year" effect appears: many firms that survive into year $t_0 + T$ cease exporting before the end of that year, so their accumulated sales are lower. This countervailing effect appears to dominate the unconditional export growth prediction in year 1 for the mean, albeit not for the median. For the mean, we can see that, contrary to the standard prediction, the model predicts the lowest growth rate for that year. From year 2 onwards, however, the standard effect prevails. To explore this issue further, Figures 11d, 11e, and 11f plot the same three moments for the growth rate in the number of shipments, which we take as a proxy for the model counterpart of the "amount of time" a firm spends over the threshold.[33] Consistent with this explanation, there is a large negative growth in the mean number of shipments during the first year.

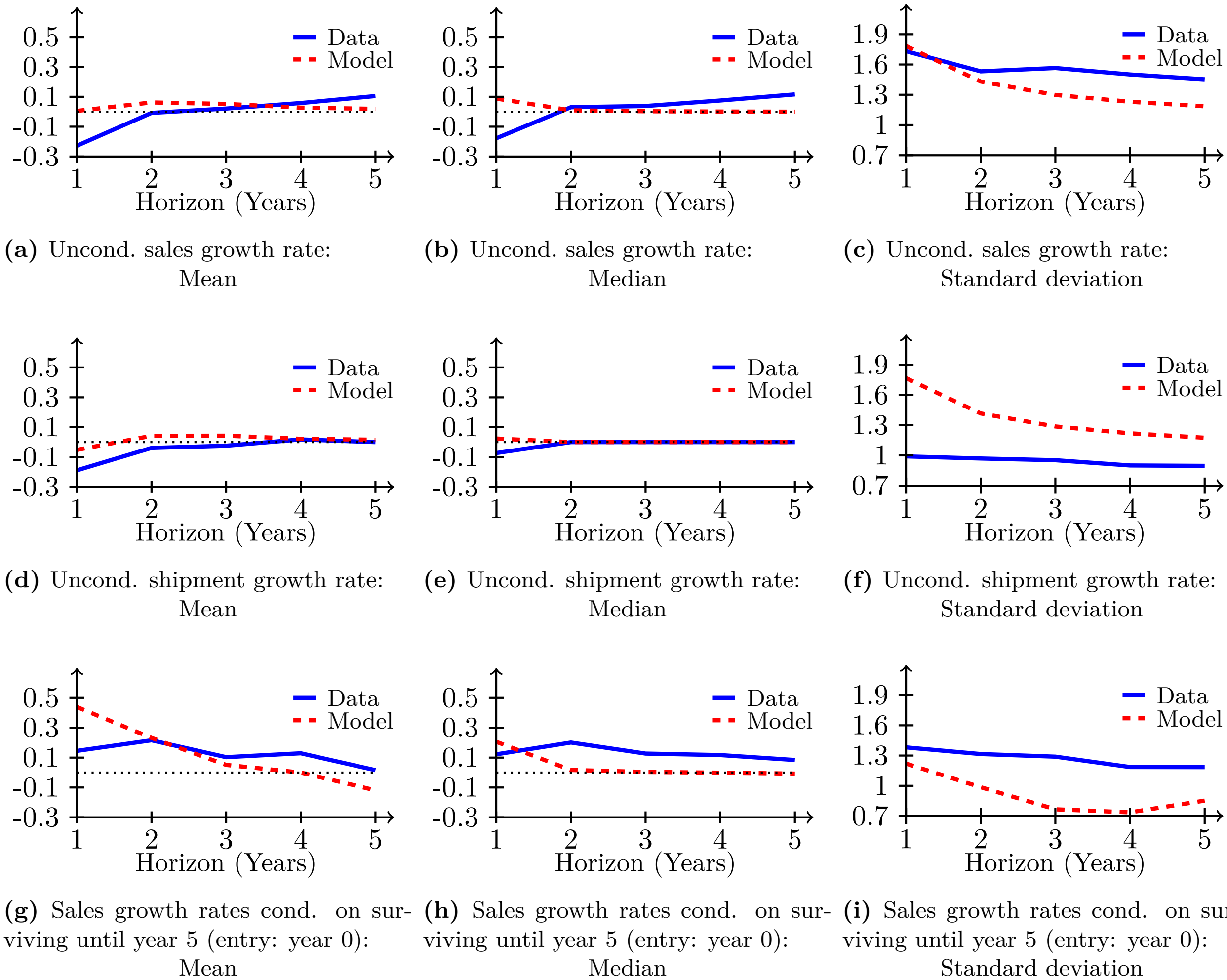
The countervailing exiting partial-year effect also holds in the data for both mean and median growth rates. In fact, in the data this is true for both the mean and median, and also appears to be driven by the unconditional shipments growth rates. Nevertheless, in contrast to the theoretical predictions, in the data this effect appears to prevail not only in year 1 but also in all subsequent years.[34]

The model matches one key fact: the decline in the standard deviation of growth rates over time (Figure 11c). The mechanism is novel. In continuous time, selection lowers the volatility of *instantaneous* growth rates (Arkolakis, 2016). But with annual data, time aggregation introduces an "intra-year" extensive-margin effect: firms near the threshold have high volatility because they are active only part-time during the year—an effect that matters most for young and small firms. This

[32] Appendix B.3 reports analogous results with calendar-year data. To compare with calendar-year data, we simulate a random variable in our model that determines the entry moment of a firm in a given calendar year. The results are similar, except that in the first year (from year 0 to year 1) we observe, both in the model and in the data, the standard partial-year effect pointed out by Bernard et al. (2017): growth rates are abnormally high since, everything else equal, firms export during a shorter amount of time in year 0.

[33] More precisely, in the model we compute $\ln(\int_{t_0+T+1}^{t_0+T+2} y(t)dt) - \ln(\int_{t_0+T}^{t_0+T+1} y(t)dt)$ and in the data $\ln(\sum_{t=t_0+T+1}^{t_0+T+2} \text{shipments}_t) - \ln(\sum_{t=t_0+T}^{t_0+T+1} \text{shipments}_t)$.

[34] The pure continuous-time formulation is partly responsible for the poor fit. Appendix I discusses an extension with lumpiness in shipments. More precisely, we enrich the model by assuming firms cannot export at every instant; rather, they can only export when they are hit by an "export opportunity" shock, which occurs with intensity η. Choosing η to get a reasonable number of shipments per year, Figure I.1 shows an improvement in the model fit.



(a) Uncond. sales growth rate: Mean

(b) Uncond. sales growth rate: Median

(c) Uncond. sales growth rate: Standard deviation

(d) Uncond. shipment growth rate: Mean

(e) Uncond. shipment growth rate: Median

(f) Uncond. shipment growth rate: Standard deviation

(g) Sales growth rates cond. on surviving until year 5 (entry: year 0): Mean

(h) Sales growth rates cond. on surviving until year 5 (entry: year 0): Median

(i) Sales growth rates cond. on surviving until year 5 (entry: year 0): Standard deviation

Figure 11: Other moments: Growth rates

time-aggregation effect is too strong in our model. Figure 11f shows that the standard deviation of shipments is significantly higher than in the data. In Appendix I, we show that the latter is due to the continuous-time formulation.[35]

Figures 11g, 11h, and 11i examine growth moments conditional on surviving five years, in the spirit of Bernard et al. (2017). The model predicts declining growth due to selection, whereas the data show a less monotonic pattern. In Appendix J, we also compute growth rate moments conditional on export-spell length, e.g. firms surviving exactly for T years, following Fitzgerald et al. (2024). The results are fairly similar: the model predicts strong growth at the beginning and a significant drop in the last period of export activity, leading to hump-shapes for $T > 3$ (see Figure J.1 in Appendix J). In the data, the strong growth at the beginning is absent.[36]

Overall, these results suggest that the restricted model can capture some broad features of exporters' growth rates, but fails in key dimensions. Instead, the results suggest considering theories where successful small firms, despite surviving longer, cannot grow as fast as a frictionless CES model would predict. For example, barriers to how fast agents may find new customers, as in Fitzgerald et al. (2024) and Eaton et al. (2025), or how fast firms can adjust their production process to satisfy demand in export markets, as in Rho and Rodrigue (2016). We leave such extensions for future research.

6.3 Moments conditional on size

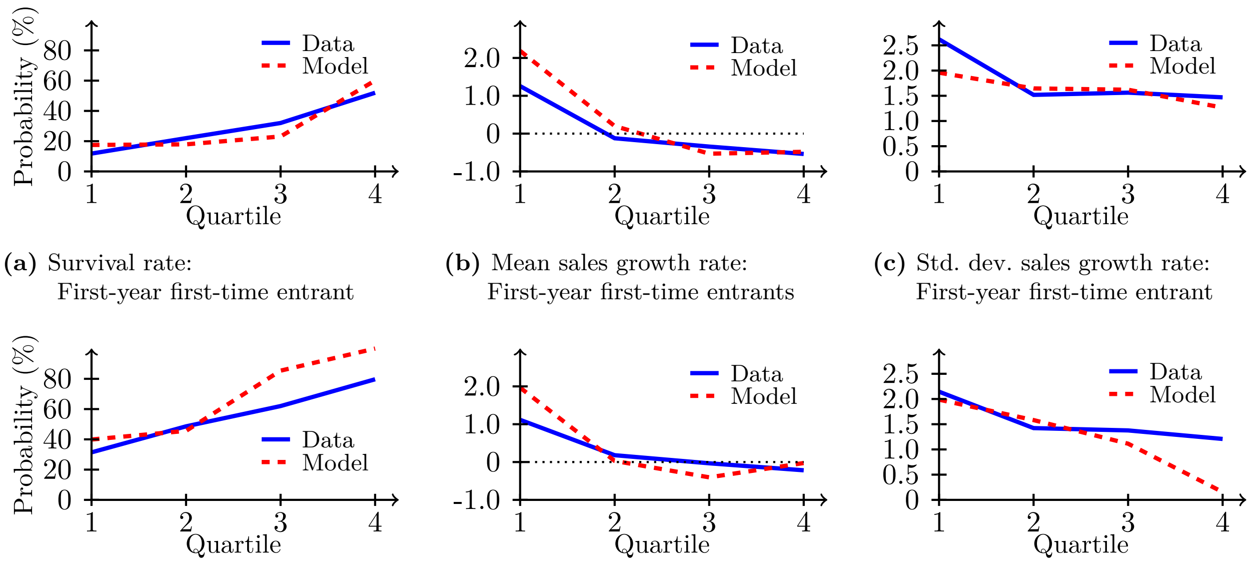
Finally, a third class of moments we consider (M_3) includes survival and growth moments conditional on size. This class of moments requires specifying, on top of the baseline model, not only a specific mapping between sales and profitability (necessary to obtain the moments in M_2) but also the distribution of the heterogeneous parameters κ and F in the population of firms. In other words, our model does not deliver predictions about this class of moments unless we are willing to make these additional distributional assumptions, which are not required to yield predictions about M_1 or M_2. In this section, we keep the assumption of CES demand and assume, in addition, that both κ and F are common across firms. As in Section 6.2, this exercise aims to assess how far this restricted version of the model can go in explaining the moments in M_3.

Figures 12a, 12b, and 12c show survival and growth moments conditional on size (quartiles of the firm size distribution) for the first-year of first-time entrants, while Figures 12d, 12e, and 12f show the same moments evaluated at the steady state distribution.[37] Even this restricted version

[35] The version of the model with lumpiness in shipments discussed in the previous footnote brings the standard deviation of shipment growth rates much closer to the data. However, it falls short of explaining the overall volatility of sales. This suggests that another economic force may be at play in the intensive margin, e.g. marketing costs as in (Arkolakis, 2010).

[36] With annual data based on calendar years, we get a hump shape driven by the well-known partial-year effect, both in the model and the data (see Appendix J).

[37] For the steady-state computation, we assume that every year N_t firms are born and that $N_{t+1} = g_B N_t$ where g_B is chosen to match the average growth rate in the number of exporters we see in our database (4.2%), as in Arkolakis (2016). We simulate firms for $T = 30$ years. Since we do not know the time of the year for the first entry, we simulate a random variable that determines it for each firm. In the data counterpart, incumbents' survival and growth moments



(a) Survival rate: First-year first-time entrant

(b) Mean sales growth rate: First-year first-time entrants

(c) Std. dev. sales growth rate: First-year first-time entrant

(d) Survival rate: Steady state

(e) Mean sales growth rate: Steady state

(f) Std. dev. sales growth rate: Steady state

Figure 12: Moments conditional on size

of the model—again, with CES demand, θ representing productivity or quality, and homogeneous κ and F—captures some broad qualitative features of the data. First, survival increases with size for first-time entrants and firms at the steady state. Second, both mean and standard deviation of sales growth rates decrease with size.[38]

Quantitatively, despite a few specific instances where mismatches are considerable, even this version of the model where we shut down heterogeneity in κ and F delivers predictions that are not far from the data, particularly in the case of survival and the standard deviation of growth rates. However, consistent with the results in the previous section, the predictions of this restricted model for mean growth rates are the least accurate. In particular, the model predicts a stronger relationship with size than the data, consistent with the idea that size is also determined by other firm characteristics unrelated to profitability, e.g. fixed-cost heterogeneity.[39]

Overall, taken together, the results of this section suggest it is useful to think in terms of a hierarchy of moments, according to which it makes sense to focus first on survival probabilities upon entry (as well as any other moments based on the extensive margin of survival). These survival

are computed using annual data based on calendar years.

[38]There is an exception in that mean growth rates are slightly larger in the fourth quartile than in the third. In unreported results, we verify that the top decile drives the non-monotonicity. The reason is related to time aggregation: as firms become very large, they are far from the threshold and, therefore, are unlikely to display fewer shipments in the year due to exit.

[39]The literature often interprets the statistical significance of both size *and* age as explanatory variables for survival and export growth as evidence of experimentation or other forms of demand learning (see, e.g. Arkolakis et al. (2018)). Our results here suggest this class of moments should be interpreted with caution. Even in a benchmark model without experimentation, if size is an imperfect proxy for firm profitability $\tilde{\theta}$ due to variation in static parameters such as F and κ, exporter age will pick up the residual variation coming from $\tilde{\theta}$.

moments are more "robust" in that they only restrict the dynamics of the profitability process while allowing for substantial flexibility in other model features we know little about. In particular, by focusing on survival, we do not need to take a stand on demand characteristics that determine the mapping between sales and profitability or on firm-destination fixed characteristics, such as demand-shifters (e.g. quality) or fixed costs, which have been shown to be relevant dimensions of heterogeneity in earlier work (Eaton et al., 2011).

7 Concluding remarks

This paper develops a model of exporter dynamics with uncertainty and experimentation. The model is parsimonious and has tractable features that allow us to characterize the solution to the firm's problem sharply. The model can rationalize two central facts about export survival in foreign markets. The first fact is that the survival profile of export first-time entrants is low and flat. The second is that re-entrants to foreign markets display higher survival rates than first-time entrants. We estimate the model, show that it can explain these facts qualitatively and quantitatively, and study its implications for a broad set of exporter dynamics moments beyond the targeted survival facts. The importance of uncertainty and experimentation in exporter dynamics is further supported by evidence that exploits hypothesized variation in the degree of uncertainty about foreign market profitability across products and distance to the destination.

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Appendix (for online publication)

A Facts in regression framework

In this section, we present the main empirical results of the paper in regression form to show that the results do not rely on composition effects. Note that since years are firm-market specific, they involve more than one calendar year. In each case, we attribute the calendar year with the largest overlap, e.g. if the firm-market-specific year is May (October) 1st 1997 - April (September) 30th 1998, then we attribute the year 1997 (1998) for the purpose of the year fixed effect. All regressions have standard errors clustered at the firm level to allow for correlation over time (i.e. different export experiences of a firm) and across markets.

Table A.1: Facts 1 and 2 controlling for composition

	(1)	(2)	(3)	(4)
	First-time entrants		Re-entrants	
Constant	0.294***		0.294***	
	(0.00455)		(0.00455)	
Year 2	-0.052***	-0.051***	-0.052***	-0.051***
	(0.00282)	(0.00355)	(0.00282)	(0.00356)
Year 3	-0.086***	-0.084***	-0.086***	-0.084***
	(0.00330)	(0.00522)	(0.00330)	(0.00523)
Year 4	-0.109***	-0.105***	-0.109***	-0.105***
	(0.00368)	(0.00673)	(0.00368)	(0.00673)
Year 5	-0.125***	-0.121***	-0.125***	-0.121***
	(0.00380)	(0.00829)	(0.00380)	(0.00824)
Year 1*Re-ent.			0.110***	0.099***
			(0.01349)	(0.01358)
Year 2*Re-ent.			0.115***	0.105***
			(0.01326)	(0.01330)
Year 3*Re-ent.			0.121***	0.109***
			(0.01325)	(0.01336)
Year 4*Re-ent.			0.105***	0.090***
			(0.01281)	(0.01317)
Year 5*Re-ent.			0.113***	0.099***
			(0.01319)	(0.01348)
Destination-year fixed effect	No	Yes	No	Yes
Product fixed effect	No	Yes	No	Yes
Observations	124275	123932	132570	132233
R^2	0.012	0.057	0.016	0.059

Notes: Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Effect of type of product on survival

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First-time entrants				Re-entrants			
Differentiated	-0.048***		-0.056***		-0.040*		-0.048**	
	(0.00868)		(0.00836)		(0.02149)		(0.02282)	
Year 1*Diff.		-0.051***		-0.060***		-0.062**		-0.077***
		(0.00929)		(0.00892)		(0.02635)		(0.02804)
Year 2*Diff.		-0.054***		-0.062***		-0.054**		-0.064**
		(0.00950)		(0.00914)		(0.02652)		(0.02841)
Year 3*Diff.		-0.048***		-0.056***		-0.019		-0.024
		(0.00951)		(0.00927)		(0.02739)		(0.02940)
Year 4*Diff.		-0.049***		-0.057***		-0.041		-0.049*
		(0.00950)		(0.00936)		(0.02730)		(0.02872)
Year 5*Diff.		-0.037***		-0.044***		-0.022		-0.026
		(0.00957)		(0.00948)		(0.02805)		(0.02929)
Destination-year fixed effect	No	No	Yes	Yes	No	No	Yes	Yes
Observations	121270	121270	120928	120928	8175	8175	8030	8030
R^2	0.015	0.015	0.034	0.034	0.011	0.011	0.089	0.089

Notes: All regressions include horizon dummies. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Effect of distance on survival

	(1)	(2)	(3)	(4)
Log(dist)*Diff.	-0.024***		-0.024***	
	(0.00449)		(0.00450)	
Log(dist)*Homog.	0.015**		0.015**	
	(0.00610)		(0.00613)	
Year 1*Diff.*Log(dist)		-0.033***		-0.033***
		(0.00565)		(0.00566)
Year 2*Diff.*Log(dist)		-0.021***		-0.021***
		(0.00549)		(0.00550)
Year 3*Diff.*Log(dist)		-0.022***		-0.022***
		(0.00514)		(0.00514)
Year 4*Diff.*Log(dist)		-0.021***		-0.021***
		(0.00519)		(0.00520)
Year 5*Diff.*Log(dist)		-0.023***		-0.023***
		(0.00502)		(0.00503)
Year 1*Homog.*Log(dist)		0.016**		0.016**
		(0.00706)		(0.00708)
Year 2*Homog.*Log(dist)		0.013*		0.014**
		(0.00704)		(0.00709)
Year 3*Homog.*Log(dist)		0.016**		0.016**
		(0.00724)		(0.00727)
Year 4*Homog.*Log(dist)		0.015**		0.015**
		(0.00674)		(0.00676)
Year 5*Homog.*Log(dist)		0.015**		0.015**
		(0.00687)		(0.00689)
Year fixed effect	No	No	Yes	Yes
Observations	120030	120030	120030	120030
R^2	0.017	0.017	0.017	0.017

Notes: All regressions include horizon dummies, a differentiated good dummy, and the interaction between a differentiated good dummy and horizon dummies (omitted). Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B Annual data based on calendar years

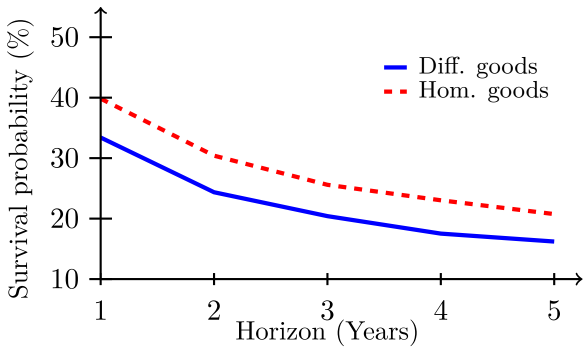
In this section, we replicate the main facts of our paper using annual data based on calendar years instead of our firm-market-specific definition of years based on the moment of the first shipment. We consider entries (firm-market level) between 1997 and 2003. An entry in year t is considered a "re-entry" if the firm has exported at least one year to the market under consideration since 1993 and did not export at $t-1$. This alternative measure is subject to time-aggregation issues (e.g. firms may enter in different months), but it has the benefit that it can be defined for incumbents as well, increasing sample size.

Table B.1: Descriptive statistics

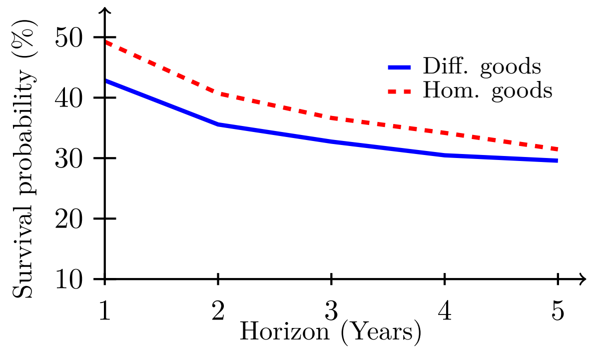
Year	Firms	Incursions	Re-entries	Incursions: 2-year surv. (%)
1997	3,775	4,081	700	25.7
1998	3,563	3,522	729	29.0
1999	3,895	4,249	1,102	27.5
2000	4,017	4,537	1,106	24.2
2001	4,347	4,244	1,175	25.9
2002	4,685	4,222	1,338	27.3
2003	5,094	4,836	1,458	27.4
Total	12772	29,691	7,608	26.6

Notes: Based on Peruvian customs dataset (World Bank).

In the model predictions, we take into account partial year effects by simulating a random variable that determines the time of the year that the firm enters. We assume this random variable is uniformly distributed over the year. Overall, we find that the partial-year effect substantially affects all moments, including survival probabilities, especially during the first year. Our partial-year correction moves moments in the same direction as in the data in all cases, but it exaggerates the magnitude of these movements in the first year.

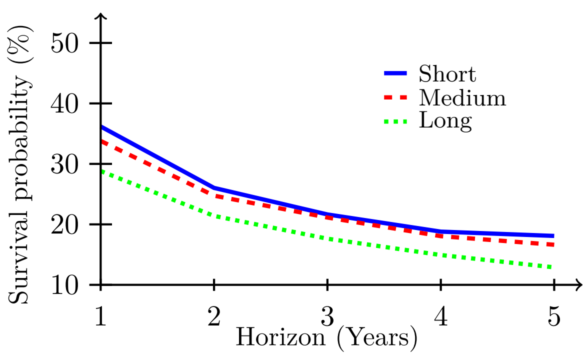


(a) First-time entrants

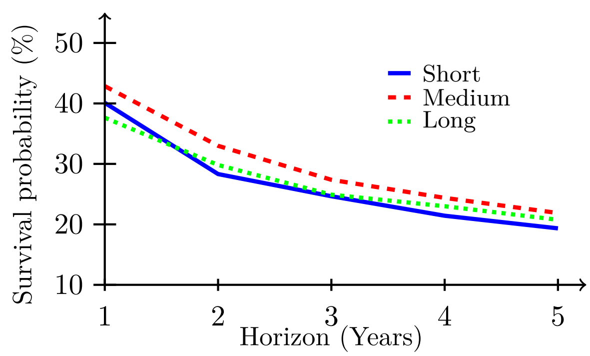


(b) Re-entrants

Figure B.1: Survival profile by type of product



(a) Differentiated goods



(b) Homogeneous goods

Figure B.2: Survival profile by distance (First-time entrants)

B.1 Main Facts

Tables B.2 to B.4, presented below, replicate tables A.1 to A.3 using annual data based on calendar years and all re-entrants, regardless of whether we observe their first-time entry.

Table B.2: Facts 1 and 2 controlling for composition

	(1)	(2)	(3)	(4)
	First-time entrants		Re-entrants	
Constant	0.357***		0.357***	
	(0.00402)		(0.00402)	
Year 2	-0.091***	-0.094***	-0.091***	-0.095***
	(0.00294)	(0.00342)	(0.00294)	(0.00338)
Year 3	-0.134***	-0.137***	-0.134***	-0.140***
	(0.00338)	(0.00468)	(0.00338)	(0.00448)
Year 4	-0.161***	-0.163***	-0.161***	-0.168***
	(0.00364)	(0.00590)	(0.00364)	(0.00555)
Year 5	-0.178***	-0.181***	-0.178***	-0.188***
	(0.00384)	(0.00740)	(0.00384)	(0.00682)
Year 1*Re-ent.			0.097***	0.084***
			(0.00722)	(0.00733)
Year 2*Re-ent.			0.111***	0.099***
			(0.00758)	(0.00754)
Year 3*Re-ent.			0.120***	0.108***
			(0.00777)	(0.00775)
Year 4*Re-ent.			0.124***	0.111***
			(0.00809)	(0.00804)
Year 5*Re-ent.			0.123***	0.111***
			(0.00822)	(0.00811)
Destination-year fixed effect	No	Yes	No	Yes
Product fixed effect	No	Yes	No	Yes
Observations	148455	148099	186495	186145
R^2	0.022	0.066	0.030	0.068

Notes: Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Effect of type of product on survival

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First-time entrants				Re-entrants			
Differentiated	-0.055***		-0.065***		-0.042***		-0.048***	
	(0.00788)		(0.00767)		(0.01300)		(0.01317)	
Year 1*Diff.		-0.064***		-0.078***		-0.064***		-0.077***
		(0.00801)		(0.00791)		(0.01341)		(0.01361)
Year 2*Diff.		-0.061***		-0.070***		-0.051***		-0.059***
		(0.00875)		(0.00853)		(0.01461)		(0.01500)
Year 3*Diff.		-0.052***		-0.061***		-0.039**		-0.044***
		(0.00900)		(0.00880)		(0.01528)		(0.01551)
Year 4*Diff.		-0.055***		-0.063***		-0.037**		-0.039**
		(0.00899)		(0.00888)		(0.01610)		(0.01640)
Year 5*Diff.		-0.045***		-0.053***		-0.019		-0.021
		(0.00904)		(0.00896)		(0.01643)		(0.01668)
Destination-year fixed effect	No	No	Yes	Yes	No	No	Yes	Yes
Observations	144910	144910	144555	144555	37145	37145	36903	36903
R^2	0.026	0.026	0.045	0.045	0.015	0.015	0.050	0.051

Notes: All regressions include horizon dummies. Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Effect of distance on survival

	(1)	(2)	(3)	(4)
Log(dist)*Diff.	-0.026***		-0.026***	
	(0.00414)		(0.00414)	
Log(dist)*Homog.	0.009		0.009	
	(0.00559)		(0.00561)	
Year 1*Diff.*Log(dist)		-0.037***		-0.036***
		(0.00527)		(0.00528)
Year 2*Diff.*Log(dist)		-0.024***		-0.024***
		(0.00502)		(0.00502)
Year 3*Diff.*Log(dist)		-0.021***		-0.021***
		(0.00504)		(0.00505)
Year 4*Diff.*Log(dist)		-0.020***		-0.020***
		(0.00480)		(0.00481)
Year 5*Diff.*Log(dist)		-0.028***		-0.028***
		(0.00467)		(0.00467)
Year 1*Homog.*Log(dist)		-0.006		-0.006
		(0.00645)		(0.00643)
Year 2*Homog.*Log(dist)		0.017***		0.018***
		(0.00665)		(0.00669)
Year 3*Homog.*Log(dist)		0.007		0.007
		(0.00660)		(0.00663)
Year 4*Homog.*Log(dist)		0.012*		0.012*
		(0.00650)		(0.00653)
Year 5*Homog.*Log(dist)		0.012*		0.012*
		(0.00664)		(0.00666)
Year fixed effect	No	No	Yes	Yes
Observations	143345	143345	143345	143345
R^2	0.028	0.028	0.028	0.028

Notes: All regressions include horizon dummies, a differentiated good dummy, and the interaction between a differentiated good dummy and horizon dummies (omitted). Standard errors are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Table B.5, we show the annualized version of the ten moments that constitute facts 1 and 2 (restricted to first-time re-entrants to isolate the implications of partial-year effects) and the corresponding model predictions using our baseline estimates.

While the partial-year effect is often discussed in relationship with growth rates (Bernard et al., 2017), we show that survival rates are also substantially affected. Indeed, first-year survival rates in the first year are about 5 percentage points higher both for first-time entrants and for re-entrants, as it is easier to survive after a month than it is to survive after an entire year. The effect gets smaller, but it is still present on longer horizons. The model also predicts higher survival probabilities but substantially overstates the partial-year effect during the first year. Since our model is cast in continuous time and firms make decisions instant-by-instant, the model does not include any reason why shipments may be spread out over time, such as inventory management by importers (Alessandria et al., 2010). This makes firms entering late into the year extremely likely to survive. Indeed, in the model, a firm entering in December has an 87% probability of surviving, while a firm entering in January survives with 31% probability. Our model is better suited for moments aggregated at a frequency where the natural delay in shipments matters less, which is why we constructed firm-market-specific years in our main analysis.[40] The model does an excellent job at horizons from year 2 onwards.

[40]See also Appendix I for a model with lumpiness.

Table B.5: Survival probabilities: Annual data

	Panel A: First-time entrants	
	Model	Data
Year 1	0.489	0.357
Year 2	0.250	0.266
Year 3	0.204	0.224
Year 4	0.187	0.196
Year 5	0.177	0.179
	Panel B: Re-entrants	
	Model	Data
Year 1	0.554	0.454
Year 2	0.366	0.372
Year 3	0.320	0.332
Year 4	0.288	0.302
Year 5	0.267	0.285

B.2 Other extensive-margin moments

We re-do here the analysis in Section 6.1 with annual data. The results are similar, except that continuous survival and the extent of re-entry are slightly larger, both in the model and in the data. The conditional survival in year 2 is farther from the data, but this mainly reflects that our model exaggerates the partial-year effect, which leads us to overestimate survival in year 1 (the denominator used to compute conditional survival).

Table B.6: Other moments: Extensive margin. Annual data.

	A: Other survival measures (entry: year 0)			
	Continuous survival		Conditional survival	
Horizon	Model	Data	Model	Data
Year 2	0.2067	0.208	0.423	0.582
Year 3	0.1380	0.146	0.667	0.701
Year 4	0.1133	0.111	0.821	0.763
Year 5	0.0999	0.091	0.882	0.818
	B: Moments conditional on exit (exit: year 0)			
	Re-entry		Survival	
Horizon	Model	Data	Model	Data
Year 2	0.081	0.108	0.081	0.108
Year 3	0.128	0.159	0.092	0.104
Year 4	0.160	0.192	0.089	0.099
Year 5	0.184	0.215	0.088	0.096

B.3 Growth rate moments

We re-do the analysis in Section 6.2 with calendar-year annual data. The results are similar, except for a sizeable partial year effect in year 1. Similar to the results on survival, our model also predicts a partial-year effect that is too large for growth. The fit to the survivors (i.e. those surviving at least six years) is now closer to the data, which is also monotonically decreasing on the horizon.

Table B.7: Other moments: Growth rates. Annual data.

	A: Unconditional sales growth rates (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	0.847	0.357	0.758	0.303	2.028	1.811
Year 2	0.024	-0.025	0.020	0.021	1.563	1.566
Year 3	0.060	0.010	0.004	0.049	1.352	1.500
Year 4	0.042	0.023	0.002	0.057	1.255	1.419
Year 5	0.011	0.090	0.000	0.108	1.228	1.496
	B: Unconditional shipment growth rates (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	0.802	0.301	0.703	0.154	2.010	1.053
Year 2	-0.014	-0.035	0.000	0.000	1.547	0.979
Year 3	0.046	-0.030	0.000	0.000	1.339	0.946
Year 4	0.035	-0.027	0.000	0.000	1.243	0.916
Year 5	0.007	-0.003	0.000	0.000	1.218	0.881
	C: Sales growth rates conditional on surviving at least until year 5 (entry: year 0)					
	Mean		Median		Std. deviation	
Horizon	Model	Data	Model	Data	Model	Data
Year 1	1.476	0.799	1.134	0.704	1.687	1.600
Year 2	0.302	0.267	0.042	0.214	1.080	1.304
Year 3	0.106	0.147	0.006	0.151	0.850	1.225
Year 4	0.007	0.073	-0.001	0.096	0.754	1.101
Year 5	-0.128	0.008	-0.007	0.079	0.903	1.186

B.4 Moments conditional on size

We re-do here the analysis in Section 6.3 with calendar-year annual data. The effect of size on survival is smaller, potentially because many small firms are now firms that enter late into the year and are very likely to survive. Indeed, according to the model, firms in the lowest quartile survive more than firms in the second quartile. The relationship with size is also weaker in the data, but the ranking is not reversed. As argued before, our partial-year-effect correction in the model for annual data based on calendar years seems to overcorrect this problem. As expected, the partial year effect also shifts upwards growth rates, which are now monotonic even in the model. In both model and data, the relationship between standard deviation and size becomes weaker, as firms may now be small because they enter late into the year.

Table B.8: Moments conditional on size. Annual data.

	First-year (first-time entrants)					
	Survival		Sales growth: mean		Sales growth: std. dev.	
Quartile	Model	Data	Model	Data	Model	Data
1	0.451	0.207	2.972	1.662	1.875	2.507
2	0.431	0.305	0.981	0.443	1.588	1.470
3	0.450	0.383	0.137	0.252	1.548	1.518
4	0.625	0.534	-0.265	-0.124	1.418	1.595

C Robustness

C.1 Other re-entrant definitions

In this section, we show the robustness of our main fact - that re-entrants survive less than first-time entrants - to several definitions of re-entrants. One worry is that the fact that shipments are discrete may lead us to falsely consider "re-entrants" firms that were not observed to export for longer than a year, but rather than having exited the market, the reason for their apparent inactivity is that they performed concentrated shipments. To address this concern, we study an alternative definition of re-entrants based on the time elapsed between re-entry and the last shipment before exit. Specifically, we call a shipment a "re-entry" if more than X months have passed since the previous shipment, where $X = 12, 18, 24$ (we also present results with annual data based on calendar years in Section B.1).

Tables C.1, C.2 and C.3 show the results with raw data. We have also verified that the results controlling for composition are similar (analogously to Table A.1). We conclude that it is very unlikely that the infrequent nature of shipments drives fact 2.

Table C.1: Survival probabilities (Raw data, 12 months)

Horizon	First-time entrants	Re-entrants
1	0.2941	0.4295
2	0.2423	0.3724
3	0.2080	0.3419
4	0.1854	0.3148
5	0.1691	0.2979

Table C.2: Survival probabilities (Raw data, 18 months)

Horizon	First-time entrants	Re-entrants
1	0.2941	0.4029
2	0.2423	0.3496
3	0.2080	0.3205
4	0.1854	0.2999
5	0.1691	0.2845

Table C.3: Survival probabilities (Raw data, 24 months)

Horizon	First-time entrants	Re-entrants
1	0.2941	0.3845
2	0.2423	0.3338
3	0.2080	0.3108
4	0.1854	0.2897
5	0.1691	0.2716

C.2 Other countries

The following tables report the survival rates of first-time entrants and re-entrants, graciously computed for us by the Exporter Dynamics Database (EDD) team at the World Bank (Fernandes et al., 2016). The sample covers twenty-two additional emerging and developing economies, as well as an extended period for Peru and is based on the recent unpublished updates to the Exporter Dynamics Database: Burundi (2013–2023), Bangladesh (2005–2016), Botswana (2004–2013), Chile (1997–2023), Colombia (1997–2023), Cabo Verde (2010–2021), Ecuador (2002–2021), Egypt (2005–2016), Gabon (2009–2021), Georgia (2000–2023), Jordan (2003–2021), Kenya (2006–2023), Morocco (2002–2013), North Macedonia (2008–2018), Montenegro (2004–2020), Malawi (2006–2021), Peru (1997–2021), Senegal (2000–2020), El Salvador (2006–2021), Serbia (2006–2019), Uruguay (2001–2023), Kosovo (2013–2023), and Zambia (2010–2021).

As in the main analysis, the time span for each country is divided into three subperiods:

- **Pre-entry period:** The first four years of the dataset, used to identify firms with no prior activity before entry.
- **Entry period:** The years between the pre-entry and post-entry periods, during which entry events are analyzed.
- **Post-entry period:** The last five years of the dataset, excluding the entry identification period to allow sufficient follow-up time for survival analysis.

For example, if the dataset spans 1993–2008:

Pre-entry: 1993–1996, Entry: 1997–2003, Post-entry: 2004–2008.

Consistent with the main text, *first-time entrants* are firms inactive in the pre-entry period that enter during the entry period. *Re-entrants* are firms that re-enter a market during the entry period after having previously exported there. *First-time re-entrants* are those re-entrants that can be observed as first-time entrants earlier in the dataset; this measure is available only for countries with sufficiently long samples (at least ten years).

Table C.4: Burundi

	First-time entrants	All re-entrants
1	0.2860	0.4138
	(0.0200)	(0.0531)
2	0.1576	0.2414
	(0.0161)	(0.0461)
3	0.0973	0.1954
	(0.0131)	(0.0428)
4	0.0914	0.1839
	(0.0127)	(0.0418)
5	0.0681	0.1954
	(0.0111)	(0.0428)
Number Firms	514	87

Table C.5: Bangladesh

	First-time entrants	All re-entrants	First-time re-entrants
1	0.4507	0.5092	0.4781
	(0.0028)	(0.0053)	(0.0198)
2	0.3169	0.3895	0.3511
	(0.0026)	(0.0052)	(0.0189)
3	0.2025	0.2449	0.0909
	(0.0023)	(0.0046)	(0.0114)
4	0.1855	0.2317	0.2743
	(0.0022)	(0.0045)	(0.0177)
5	0.1771	0.2381	0.2649
	(0.0022)	(0.0045)	(0.0175)
Number Firms	3.11e+04	8886	638

Table C.6: Botswana

	First-time entrants	All re-entrants
1	0.3180	0.5482
	(0.0144)	(0.0274)
2	0.2056	0.4066
	(0.0125)	(0.0270)
3	0.1710	0.3946
	(0.0117)	(0.0269)
4	0.1412	0.3373
	(0.0108)	(0.0260)
5	0.1412	0.2771
	(0.0108)	(0.0246)
Number Firms	1041	332

Table C.7: Chile

	First-time entrants	All re-entrants	First-time re-entrants
1	0.3734	0.4708	0.4484
	(0.0015)	(0.0022)	(0.0032)
2	0.2873	0.4013	0.3681
	(0.0014)	(0.0021)	(0.0031)
3	0.2457	0.3605	0.3263
	(0.0013)	(0.0021)	(0.0030)
4	0.2166	0.3311	0.2998
	(0.0013)	(0.0020)	(0.0030)
5	0.1940	0.3070	0.2733
	(0.0012)	(0.0020)	(0.0029)
Number Firms	1.08e+05	5.30e+04	2.39e+04

Table C.8: Colombia

	First-time entrants	All re-entrants	First-time re-entrants
1	0.3735	0.4749	0.4385
	(0.0015)	(0.0022)	(0.0033)
2	0.2766	0.3953	0.3570
	(0.0013)	(0.0022)	(0.0032)
3	0.2310	0.3566	0.3146
	(0.0013)	(0.0021)	(0.0031)
4	0.2021	0.3245	0.2833
	(0.0012)	(0.0021)	(0.0030)
5	0.1799	0.3017	0.2592
	(0.0012)	(0.0020)	(0.0029)
Number Firms	1.11e+05	5.08e+04	2.29e+04

Table C.9: Cabo Verde

	First-time entrants	All re-entrants	First-time re-entrants
1	0.2500	0.3214	0.5000
	(0.0343)	(0.0899)	(0.5000)
2	0.1500	0.2500	0.0000
	(0.0283)	(0.0833)	(0.0000)
3	0.1187	0.1429	0.0000
	(0.0257)	(0.0673)	(0.0000)
4	0.1000	0.1429	0.0000
	(0.0238)	(0.0673)	(0.0000)
5	0.0688	0.1071	0.0000
	(0.0201)	(0.0595)	(0.0000)
Number Firms	160	28	2

Table C.10: Ecuador

	First-time entrants	All re-entrants	First-time re-entrants
1	0.4452	0.5178	0.5084
	(0.0023)	(0.0041)	(0.0060)
2	0.3395	0.4355	0.4112
	(0.0022)	(0.0040)	(0.0059)
3	0.2899	0.4008	0.3800
	(0.0021)	(0.0040)	(0.0058)
4	0.2579	0.3626	0.3447
	(0.0020)	(0.0039)	(0.0057)
5	0.2349	0.3387	0.3158
	(0.0020)	(0.0038)	(0.0056)
Number Firms	4.66e+04	1.52e+04	6997

Table C.11: Egypt, Arab Republic

	First-time entrants	All re-entrants	First-time re-entrants
1	0.3650	0.4330	0.4236
	(0.0028)	(0.0048)	(0.0197)
2	0.2692	0.3517	0.3631
	(0.0026)	(0.0046)	(0.0192)
3	0.2349	0.3132	0.3248
	(0.0025)	(0.0045)	(0.0187)
4	0.2104	0.2835	0.2962
	(0.0024)	(0.0044)	(0.0182)
5	0.1833	0.2533	0.2691
	(0.0022)	(0.0042)	(0.0177)
Number Firms	2.98e+04	1.07e+04	628

Table C.12: Gabon

	First-time entrants	All re-entrants	First-time re-entrants
1	0.2020	0.3854	0.2889
	(0.0064)	(0.0137)	(0.0339)
2	0.1377	0.3105	0.2056
	(0.0055)	(0.0131)	(0.0302)
3	0.1029	0.2596	0.2056
	(0.0048)	(0.0124)	(0.0302)
4	0.0815	0.1998	0.1667
	(0.0043)	(0.0113)	(0.0279)
5	0.0695	0.1736	0.1222
	(0.0040)	(0.0107)	(0.0245)
Number Firms	3986	1256	180

Table C.13: Georgia

	First-time entrants	All re-entrants	First-time re-entrants
1	0.3270	0.4620	0.4525
	(0.0020)	(0.0051)	(0.0057)
2	0.2103	0.3362	0.3258
	(0.0017)	(0.0048)	(0.0054)
3	0.1526	0.2636	0.2562
	(0.0015)	(0.0045)	(0.0050)
4	0.1201	0.2429	0.2308
	(0.0014)	(0.0043)	(0.0048)
5	0.1052	0.2161	0.2041
	(0.0013)	(0.0042)	(0.0046)
Number Firms	5.69e+04	9738	7569

Table C.14: Jordan

	First-time entrants	All re-entrants	First-time re-entrants
1	0.3869	0.4384	0.4081
	(0.0031)	(0.0060)	(0.0092)
2	0.2868	0.3441	0.3197
	(0.0029)	(0.0058)	(0.0088)
3	0.2258	0.2921	0.2637
	(0.0027)	(0.0055)	(0.0083)
4	0.1925	0.2571	0.2479
	(0.0025)	(0.0053)	(0.0081)
5	0.1700	0.2259	0.2173
	(0.0024)	(0.0051)	(0.0077)
Number Firms	2.45e+04	6734	2840

Table C.15: Kenya

	First-time entrants	All re-entrants	First-time re-entrants
1	0.3226	0.4505	0.5152
	(0.0026)	(0.0048)	(0.0074)
2	0.2316	0.3656	0.4269
	(0.0024)	(0.0047)	(0.0074)
3	0.2251	0.3162	0.3751
	(0.0023)	(0.0045)	(0.0072)
4	0.2016	0.2875	0.3543
	(0.0022)	(0.0044)	(0.0071)
5	0.1810	0.2619	0.3200
	(0.0022)	(0.0043)	(0.0069)
Number Firms	3.18e+04	1.07e+04	4519

Table C.16: Morocco

	First-time entrants	All re-entrants	First-time re-entrants
1	0.3415	0.4386	0.3853
	(0.0040)	(0.0078)	(0.0270)
2	0.2514	0.3617	0.3242
	(0.0037)	(0.0076)	(0.0259)
3	0.1891	0.3102	0.2385
	(0.0033)	(0.0073)	(0.0236)
4	0.1597	0.2532	0.2171
	(0.0031)	(0.0069)	(0.0228)
5	0.1429	0.2420	0.2630
	(0.0030)	(0.0068)	(0.0244)
Number Firms	1.40e+04	4017	327

Table C.17: North Macedonia

	First-time entrants	All re-entrants
1	0.3504	0.4520
	(0.0065)	(0.0118)
2	0.2721	0.3926
	(0.0060)	(0.0116)
3	0.2378	0.3612
	(0.0058)	(0.0114)
4	0.2147	0.3292
	(0.0056)	(0.0111)
5	0.1978	0.3107
	(0.0054)	(0.0110)
Number Firms	5425	1783

Table C.18: Montenegro

	First-time entrants	All re-entrants	First-time re-entrants
1	0.2884	0.4070	0.3868
	(0.0053)	(0.0099)	(0.0144)
2	0.2252	0.3458	0.3214
	(0.0049)	(0.0096)	(0.0138)
3	0.1941	0.3316	0.3092
	(0.0046)	(0.0095)	(0.0136)
4	0.1729	0.3101	0.2857
	(0.0044)	(0.0093)	(0.0133)
5	0.1582	0.2846	0.2666
	(0.0043)	(0.0091)	(0.0131)
Number Firms	7306	2467	1148

Table C.19: Malawi

	First-time entrants	All re-entrants	First-time re-entrants
1	0.1828 (0.0056)	0.3950 (0.0134)	0.3224 (0.0269)
2	0.1145 (0.0046)	0.3195 (0.0128)	0.2171 (0.0237)
3	0.0828 (0.0040)	0.2923 (0.0125)	0.1875 (0.0224)
4	0.0693 (0.0037)	0.2319 (0.0116)	0.1711 (0.0216)
5	0.0622 (0.0035)	0.2394 (0.0117)	0.1908 (0.0226)
Number Firms	4759	1324	304

Table C.20: Peru (longer sample)

	First-time entrants	All re-entrants	First-time re-entrants
1	0.3733 (0.0016)	0.4627 (0.0028)	0.4382 (0.0040)
2	0.2686 (0.0015)	0.3900 (0.0027)	0.3588 (0.0038)
3	0.2184 (0.0014)	0.3484 (0.0027)	0.3144 (0.0037)
4	0.1867 (0.0013)	0.3172 (0.0026)	0.2809 (0.0036)
5	0.1632 (0.0012)	0.2957 (0.0026)	0.2584 (0.0035)
Number Firms	9.02e+04	3.16e+04	1.58e+04

Table C.21: Senegal

	First-time entrants	All re-entrants	First-time re-entrants
1	0.2898 (0.0039)	0.4115 (0.0068)	0.3925 (0.0098)
2	0.2160 (0.0035)	0.3371 (0.0065)	0.3033 (0.0092)
3	0.1786 (0.0033)	0.2874 (0.0062)	0.2610 (0.0088)
4	0.1530 (0.0031)	0.2566 (0.0060)	0.2295 (0.0084)
5	0.1400 (0.0030)	0.2354 (0.0058)	0.2033 (0.0081)
Number Firms	1.35e+04	5268	2479

Table C.22: El Salvador

	First-time entrants	All re-entrants	First-time re-entrants
1	0.3415	0.4681	0.4398
	(0.0047)	(0.0068)	(0.0146)
2	0.2543	0.4042	0.3723
	(0.0043)	(0.0067)	(0.0142)
3	0.2270	0.3675	0.3351
	(0.0042)	(0.0066)	(0.0139)
4	0.1992	0.3387	0.2944
	(0.0040)	(0.0065)	(0.0134)
5	0.1833	0.3260	0.2961
	(0.0039)	(0.0064)	(0.0134)
Number Firms	1.01e+04	5383	1155

Table C.23: Serbia

	First-time entrants	All re-entrants	First-time re-entrants
1	0.3782	0.4713	0.4431
	(0.0021)	(0.0033)	(0.0077)
2	0.2958	0.4120	0.3918
	(0.0019)	(0.0033)	(0.0076)
3	0.2568	0.3788	0.3514
	(0.0018)	(0.0032)	(0.0074)
4	0.2353	0.3578	0.3237
	(0.0018)	(0.0032)	(0.0073)
5	0.2177	0.3326	0.3079
	(0.0017)	(0.0032)	(0.0072)
Number Firms	5.58e+04	2.23e+04	4112

Table C.24: Uruguay

	First-time entrants	All re-entrants	First-time re-entrants
1	0.3322	0.4537	0.4205
	(0.0036)	(0.0051)	(0.0081)
2	0.2528	0.3745	0.3270
	(0.0033)	(0.0049)	(0.0077)
3	0.2123	0.3327	0.2928
	(0.0031)	(0.0048)	(0.0075)
4	0.1884	0.3025	0.2584
	(0.0030)	(0.0047)	(0.0072)
5	0.1693	0.2799	0.2416
	(0.0028)	(0.0046)	(0.0070)
Number Firms	1.75e+04	9630	3712

Table C.25: Kosovo

	First-time entrants	All re-entrants
1	0.3370	0.4600
	(0.0088)	(0.0190)
2	0.2808	0.3755
	(0.0083)	(0.0185)
3	0.2815	0.3741
	(0.0083)	(0.0185)
4	0.2917	0.3581
	(0.0084)	(0.0183)
5	0.2688	0.3464
	(0.0082)	(0.0182)
Number Firms	2917	687

Table C.26: Zambia

	First-time entrants	All re-entrants	First-time re-entrants
1	0.2701	0.4124	0.3548
	(0.0072)	(0.0174)	(0.0613)
2	0.1810	0.3342	0.2258
	(0.0062)	(0.0166)	(0.0535)
3	0.1552	0.3056	0.3065
	(0.0059)	(0.0162)	(0.0590)
4	0.1334	0.2609	0.2258
	(0.0055)	(0.0155)	(0.0535)
5	0.1273	0.2398	0.2903
	(0.0054)	(0.0151)	(0.0581)
Number Firms	3802	805	62

D General model, proofs and derivations

D.1 Derivation of HJB equations

The experienced firm An experienced firm receives profits given by $\pi_e(\theta_t;\psi) = \psi\kappa\theta_t - F = F\left(\psi\tilde{\theta}_t - 1\right)$ if it exports and 0 otherwise. The value of an experienced firm (V_e) at $t = 0$ is the solution to the following problem:

$$V_e(\tilde{\theta}_0;\psi) = \sup_{\{y_e(\tilde{\theta}_t)\}_{t=0}^{\infty}} \mathbb{E}\left(\int_0^{\infty} e^{-rt}F\left(\psi\tilde{\theta}_t - 1\right) y_e(\tilde{\theta}_t)dt\right)$$

subject to (1) with $\tilde{\theta}_0$ given, where r is the discount rate.

Suppose a firm follows any constant policy $y_e \in \{0,1\}$ during an interval of time $[t, t+\tau]$. Exploiting the stationarity of the problem, we can write the problem recursively as

$$V_e(\tilde{\theta}_t;\psi) = \max_{y_e\in\{0,1\}} \mathbb{E}\left(\int_0^{\tau} e^{-rs}F\left(\psi\tilde{\theta}_{t+s} - 1\right) y_e ds + e^{-r\tau}V_e(\tilde{\theta}_{t+\tau};\psi)\right).$$

Taking the limit $\tau \to 0$ and rearranging yields (2).

The inexperienced firm First, we make a technical assumption so that the inexperienced firms' problem is well-defined: we assume that the distribution of ψ is such that $\mathbb{E}_{\psi}V_e(\tilde{\theta};\psi)$ satisfies a polynomial growth condition.[41] Let t denote the (random) time at which a firm becomes experienced. Given that this event occurs with intensity λ only if the firm exports, the probability density function (p.d.f) of t depends on the export policy. At time $t = 0$, this density is given by $\lambda y_i(\tilde{\theta}_t)e^{-\int_0^t \lambda y_i(\tilde{\theta}_s)ds}$, where the exponent term captures the probability that the shock did not take place until t and $\lambda y_i(\tilde{\theta}_t)$ is the instantaneous arrival rate. Then, the inexperienced firm's problem can be written as

$$V_i(\tilde{\theta}_0) = \sup_{\{y_i(\tilde{\theta}_t)\}_{t=0}^{\infty}} \mathbb{E}\int_0^{\infty}\left[\int_0^t e^{-ru}F\left(\tilde{\theta}_u - 1\right) y_i(\tilde{\theta}_u)du + e^{-rt}\mathbb{E}V_e(\tilde{\theta}_t;\psi)\right]\lambda y_i(\tilde{\theta}_t)e^{-\int_0^t \lambda y_i(\tilde{\theta}_s)ds}dt \tag{D.1}$$

subject to (1) with $\tilde{\theta}_0$ given. Fixing a time t at which the firm receives the shock, the term in square brackets in (D.1) captures the expected discounted profits, which consist of the discounted stream of net profit flows $F\left(\tilde{\theta}_u - 1\right)du$ accumulated during export periods up to t and the discounted expected value of being an experienced firm. Note that by exporting the firm may become experienced sooner, which is always desirable because it implies a higher profit flow on average.

[41]We say that $f : [0,\infty) \to$ satisfies a polynomial growth condition if there exist $M > 0$ and $\nu > 0$ such that $|f(\theta)| \leq M(1+\theta^{\nu})$. Since $\tilde{\theta}$ is a GBM, it is easy to see that V_e is a power function. Thus, when ψ is Pareto, this is akin to a lower bound on α to guarantee that the expectation is finite.

Manipulating (D.1), we can rewrite the inexperienced firm's problem as[42]

$$V_i(\tilde{\theta}_0) = \sup_{\{y_i(\tilde{\theta}_t)\}_{t=0}^{\infty}} \mathbb{E} \int_0^{\infty} e^{-rt-\lambda \int_0^t y_i(\tilde{\theta}_s)ds} \left\{ F\left(\tilde{\theta}_t - 1\right) + \lambda \mathbb{E}_{\psi} V_e(\tilde{\theta}_t) \right\} y_i(\tilde{\theta}_t) dt \tag{D.2}$$

subject to (1) and $\tilde{\theta}_0$ given. Consider a firm that follows any constant policy $y_i \in \{0,1\}$ during an interval of time $[t, t+\tau]$. Exploiting the stationarity of problem (D.2) we can write it recursively as

$$V_i(\tilde{\theta}_t) = \max_{y_i \in \{0,1\}} \mathbb{E} \left(\int_0^{\tau} e^{-(r+\lambda y_i)s} \left\{ F\left(\tilde{\theta}_{t+s} - 1\right) + \lambda \mathbb{E}_{\psi} V_e(\tilde{\theta}_{t+s}; \psi) \right\} y_i ds + e^{-(r+\lambda y_i)\tau} V_i(\tilde{\theta}_{t+\tau}) \right). \tag{D.3}$$

Taking the limit $\tau \to 0$ and rearranging yields (3).

D.2 Proof of Proposition 1

We prove the result under the general conditions on the profit function $\pi(\cdot)$, the law of motion of profitability, θ_t, and distribution ψ stated below:

Assumption 1. *$\mathbb{E}_{\psi}\pi_e(\psi, \theta) \geq \pi_i(\theta)\, \forall \theta \pi_e$ is continuous, π_i belongs to C^2 and both are weakly increasing in $\theta \forall \psi$. ψ and θ are independent.*

Assumption 2. *Let $h \equiv \lambda \mathbb{E}_{\psi}\left(\max\left\{\pi_e(\theta;\psi), 0\right\}\right) - \lim_{dt \to 0}\left\{\mathbb{E}(e^{-rdt}\pi_i(\theta_{t+dt})) - \pi_i(\theta_t)\right\}$. If $\lambda > 0$, $h(\theta)$ is weakly increasing in θ. Furthermore, $E\left[\int_0^{\infty} e^{-rt} h(\theta_t) d\theta_t | \theta_0\right]$ satisfies a polynomial growth condition.*[43]

Assumption 3. *There exists $\bar{\theta}$ such that $\forall \theta > \bar{\theta}$, flow profits are positive even for inexperienced firms, $\pi_i(\theta) \geq 0$.*

Assumption 4. *The profitability process $\{\theta_t\}_{t=0}^{\infty}$ is assumed to follow a diffusion,*

$$d\theta_t = \mu_{\theta} dt + \sigma_{\theta} dZ_t \tag{D.4}$$

where Z_t is a standard brownian motion. We assume μ_{θ} and σ_{θ} are continuous functions of θ that satisfy Lipschitz and growth conditions on μ and σ.[44] *Furthermore, if $\theta'' > \theta'$, then $F(\theta|\theta'') \succsim_{FOSD} F(\theta|\theta')$.*

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[42] Distribute the term $\lambda y_i(\tilde{\theta}_t) e^{-\lambda \int_0^t y_i(\tilde{\theta}_s)ds}$ inside the parenthesis and note that $\int_0^{\infty}\int_0^t e^{-ru-\lambda \int_0^t y_i(\tilde{\theta}_s)ds} \lambda y_i(\tilde{\theta}_t) F\left(\tilde{\theta}_u - 1\right) y_i(\tilde{\theta}_u) du dt = \int_0^{\infty}\int_s^{\infty} e^{-ru-\lambda \int_0^t y_i(\tilde{\theta}_s)ds} \lambda y_i(\tilde{\theta}_t) dt F\left(\tilde{\theta}_u - 1\right) y_i(\tilde{\theta}_u) du = \int_0^{\infty} e^{-ru-\lambda \int_0^u y_i(\tilde{\theta}_s)ds} F\left(\tilde{\theta}_u - 1\right) y_i(\tilde{\theta}_u) du$.

[43] We say that $f : [0,\infty) \to \mathbb{R}$ satisfies a polynomial growth condition if there exist $M > 0$ and $\nu > 0$ such that $|f(\theta)| \leq M(1 + \theta^{\nu})$.

[44] We say that μ satisfies a Lipschitz condition if there exists $k > 0$ such that

$$\left|\mu(\theta) - \mu\left(\theta'\right)\right| \leq k\left|\theta - \theta'\right|.$$

This ensures the existence of a strong solution to (D.4).

Assumption 5. *$\mathbb{E}_\psi V_e$ satisfies a polynomial growth condition $\forall\theta$.*

Assumption 1 is satisfied in the model in the text because $\mathbb{E}(\psi) \geq 1$. Applying Ito's Lemma to Assumption 2 we get

$$h \equiv \lambda \mathbb{E}_\psi \pi_e(\theta;\psi) + r\pi_i(\theta) - \mu_\theta \frac{d\pi_i(\theta)}{d\theta} - \frac{1}{2}\sigma_\theta^2 \frac{d^2\pi_i}{d\theta^2}$$

In the model in the text,

$$h \equiv \mathbb{E}_\psi \left[\max\left\{\psi\tilde{\theta} - 1, 0\right\}\right] + \frac{r}{\lambda}\left(\tilde{\theta} - 1\right) - \frac{\tilde{\theta}}{\lambda}\left(\mu + \frac{1}{2}\sigma^2\right)$$

which is clearly increasing in $\tilde{\theta}$ (recall $r > \mu + \frac{1}{2}\sigma^2 > 0$). Furthermore, Assumption 3 is satisfied by taking $\bar{\theta} = \frac{F}{\kappa}$ and Assumption 4 is satisfied by the GBM assumption ($\mu_\theta = (\mu + \frac{1}{2}\sigma^2)\theta$ and $\sigma_\theta = \sigma\theta$). Finally, when ψ is distributed Pareto, one can show that

$$\mathbb{E}_\psi V_e(\tilde{\theta}) = F \begin{cases} \frac{2}{(\alpha-1)(\beta_1-\alpha)(\alpha-\beta_2)\sigma^2}\tilde{\theta}^\alpha - \frac{A_{e1}\alpha}{\beta_1-\alpha}\tilde{\theta}^{\beta_1} & \text{if } \tilde{\theta} < 1 \\ \frac{\alpha A_{e2}}{\alpha-\beta_2}\tilde{\theta}^{\beta_2} + \frac{\alpha}{(r-\mu')(\alpha-1)}\tilde{\theta} - \frac{1}{r} & \text{if } \tilde{\theta} \geq 1 \end{cases},$$

for some constants A_{e1} and A_{e2}. This expression satisfies a polynomial growth condition, i.e. Assumption 5 is satisfied.

First, we prove the following result,

Lemma 1. *Exporting is optimal for an inexperienced firm when $\theta > \bar{\theta}$.*

Proof. Exporting while $\theta > \bar{\theta}$ yields flow profits $\pi_i(\theta) \geq 0$ in $[\bar{\theta}, +\infty)$ if the firm remains inexperienced and introduces the possibility of becoming experienced, which, by assumption 1, increases expected profits. Hence, exporting is optimal in this region. □

Define $\pi^{EE}(\theta) \equiv \mathbb{E}_\psi(\max\{\pi_e(\theta,\psi), 0\})$. Note that the flow benefits of exporting (W) are given by

$$W = \pi_i + \lambda(\mathbb{E}_\psi V_e - V_i).$$

Since y_i is piecewise continuous, V_i is continuous. Given that π_i and V_e are continuous, this implies W is continuous. Assuming an indifferent firm exports, a firm will export iff $W \geq 0$. By Assumption 1 and the possibility of inaction, we know that $0 \leq V_i(\theta) \leq V_e(\theta) < \infty\ \forall\theta$. Moreover, since W is continuous and π_e and π_i are continuous, by the Feynman-Kac Theorem we know that $V_i, V_e \in C^2$ and, thus, $W \in C^2$. Hence, V_e and V_i satisfy the following Hamilton-Jacobi-Bellman equations,

$$r\mathbb{E}_\psi V_e = \pi^{EE} + \mu_\theta \frac{d\mathbb{E}_\psi V_e}{d\theta} + \frac{1}{2}\sigma_\theta^2 \frac{d^2\mathbb{E}_\psi V_e}{d\theta^2}\ \forall\theta \quad \text{(D.5)}$$

$$(r+\lambda)V_i = \pi_i + \lambda \mathbb{E}_\psi V_e + \mu_\theta \frac{dV_i}{d\theta} + \frac{1}{2}\sigma_\theta^2 \frac{d^2 V_i}{d\theta^2} \text{ when } W(\theta) \geq 0 \tag{D.6}$$

$$rV_i = \mu_\theta \frac{dV_i}{d\theta} + \frac{1}{2}\sigma_\theta^2 \frac{dV_i}{d\theta} \text{ when } W(\theta) < 0 \tag{D.7}$$

Next, subtract (D.6) and (D.7) from (D.5) to obtain,

$$(r+\lambda)(\mathbb{E}_\psi V_e - V_i) = \pi^{EE} - \pi_i + \mu_\theta \left(\frac{d\mathbb{E}_\psi V_e}{d\theta} - \frac{dV_i}{d\theta}\right) + \frac{\sigma_\theta^2}{2}\left(\frac{d^2 \mathbb{E}_\psi V_e}{d\theta^2} - \frac{d^2 V_i}{d\theta^2}\right) \text{ when } W(\theta) \geq 0 \tag{D.8}$$

$$r(\mathbb{E}_\psi V_e - V_i) = \pi^{EE} + \mu_\theta \left(\frac{d\mathbb{E}_\psi V_e}{d\theta} - \frac{dV_i}{d\theta}\right) + \frac{\sigma_\theta^2}{2}\left(\frac{d^2 \mathbb{E}_\psi V_e}{d\theta^2} - \frac{d^2 V_i}{d\theta^2}\right) \text{ when } W(\theta) < 0 \tag{D.9}$$

Rewrite (D.8) and (D.9) in terms of W to obtain

$$\left(\frac{r+\lambda}{\lambda}\right)(W - \pi_i) = \pi^{EE} - \pi_i + \frac{\mu_\theta}{\lambda}\left(\frac{dW}{d\theta} - \frac{d\pi_i}{d\theta}\right) + \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\left(\frac{d^2 W}{d\theta^2} - \frac{d^2 \pi_i}{d\theta^2}\right) \text{ when } W(\theta) \geq 0$$

$$\left(\frac{r}{\lambda}\right)(W - \pi_i) = \pi^{EE} + \frac{\mu_\theta}{\lambda}\left(\frac{dW}{d\theta} - \frac{d\pi_i}{d\theta}\right) + \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\left(\frac{d^2 W}{d\theta^2} - \frac{d^2 \pi_i}{d\theta^2}\right) \text{ when } W(\theta) < 0$$

where we used the fact that $\pi_i \in C^2$. Rearranging,

$$\left(1+\frac{r}{\lambda}\right)W = \pi^{EE} + \frac{r}{\lambda}\pi_i - \frac{\mu_\theta}{\lambda}\frac{d\pi_i}{d\theta} - \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2\pi_i}{d\theta^2} + \frac{\mu_\theta}{\lambda}\frac{dW}{d\theta} + \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2 W}{d\theta^2} \text{ when } W(\theta) \geq 0$$

$$\left(1+\frac{r}{\lambda}\right)W = W + \pi^{EE} + \frac{r}{\lambda}\pi_i - \frac{\mu_\theta}{\lambda}\frac{d\pi_i}{d\theta} - \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2\pi_i}{d\theta^2} + \frac{\mu_\theta}{\lambda}\frac{dW}{d\theta} + \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2 W}{d\theta^2} \text{ when } W(\theta) < 0.$$

Define $h \equiv \pi^{EE} + \frac{r}{\lambda}\pi_i - \frac{\mu_\theta}{\lambda}\frac{d\pi^I}{d\theta} - \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2\pi_i}{d\theta^2}$, which is exactly Assumption 2 after applying Ito's Lemma. We can rewrite this as

$$\left(1+\frac{r}{\lambda}\right)W = W\mathbf{1}_{W<0} + h + \frac{\mu_\theta}{\lambda}\frac{dW}{d\theta} + \frac{1}{2}\frac{\sigma_\theta^2}{\lambda}\frac{d^2 W}{d\theta^2}. \tag{D.10}$$

By assumptions 2 and 5, we know that W and h satisfy a polynomial growth condition. Furthermore, we know that W is continuous. Hence, by Feynman-Kac theorem (Duffie, Appendix E, p.344), the unique solution that satisfies a polynomial growth condition to (D.10) is given by

$$W(\theta_0) = \mathbb{E}\left(\int_0^\infty e^{-\left(1+\frac{r}{\lambda}\right)t}\left\{W(\theta_t)\mathbf{1}_{W(\theta_t)<0} + h(\theta_t)\right\} d\theta_t | \theta_0\right). \tag{D.11}$$

We still need to show such a solution exists. We do this next.

Lemma 2. *There is a unique continuous solution W to the functional equation* (D.11)*.*

Proof. By Lemma 1, the solution satisfies $W(\theta) \geq 0$ for $\theta_t > \bar{\theta}$. Since only $W(\theta) < 0$ appears on the RHS of the functional equation (D.11), we can focus our attention on the set $[0, \bar{\theta}]$. Define the

operator $T : C(X) \to C(X)$ as the RHS on (D.11) restricted to $\left[0, \bar{\theta}\right]$, where C is the space of continuous and bounded functions. Note that T is well-defined in the sense that if $f \in C$, $Tf \in C$. Next, we show that T satisfies monotonicity and discounting:
(i) Monotonicity. Take $f \geq g$. Then,

$$\begin{aligned} Tf(\theta_0) &= \mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\{f(\theta_t)\mathbf{1}_{f(\theta_t)<0\cap\theta_t<\bar{\theta}} + h(\theta_t)\}d\theta_t|\theta_0] \\ &\geq \mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\{g(\theta_t)\mathbf{1}_{f(\theta_t)<0\cap\theta_t<\bar{\theta}} + h(\theta_t)\}d\theta_t|\theta_0] \\ &\geq \mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\{g(\theta_t)\mathbf{1}_{g(\theta_t)<0\cap\theta_t<\bar{\theta}} + h(\theta_t)\}d\theta_t|\theta_0] = Tg(\theta_0). \end{aligned}$$

The first step uses $f \geq g$, while the second step uses the fact that if $f(z) < 0 \Rightarrow g(z) < 0$ so $g(z)\, 1_{g(z)<0} = g(z)\, 1_{f(z)<0} + g(z)\, 1_{f(z)\geq 0 \cap g(z)<0} \leq g(z)\, 1_{f(z)<0}$.
(ii) Discounting. Take $a > 0$. Then,

$$\begin{aligned} T(f(\theta_0)+a) &= \mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\{(f(\theta_t)+a)\mathbf{1}_{f(\theta_t)+a<0\cap\theta_t<\bar{\theta}} + h(\theta_t)\}d\theta_t|\theta_0] \\ &= \mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\{(f(\theta_t)+a)\mathbf{1}_{f(\theta_t)<0\cap\theta_t<\bar{\theta}} + h(\theta_t) - (f(\theta_t)+a)\mathbf{1}_{-a\leq f(\theta_t)<0\cap\theta_t<\bar{\theta}}\}d\theta_t|\theta_0] \\ &\leq Tf(\theta_0) + a\mathbb{E}[\int_0^\infty e^{-(1+\frac{r}{\lambda})}\mathbf{1}_{f(\theta_t)<0\cap\theta_t<\bar{\theta}}d\theta_t|\theta_0] \\ &\leq Tf(\theta_0) + \frac{a}{1+\frac{r}{\lambda}}. \end{aligned}$$

Since $r > 0$ by Assumption 5, the result follows. Thus, by Blackwell's theorem $T : C(X) \to C(X)$ is a contraction. Since $W_{[0,\bar{\theta}]} \in C(X)$, by the contraction mapping theorem, there exists a unique continuous $W : [0, \bar{\theta}] \to$ that solves (D.11). Given this, $W(\theta)$ for $\theta > \bar{\theta}$ is uniquely defined from (D.11). □

Lemma 3. *W is weakly increasing.*

Proof. Take some weakly increasing function f and apply T for $\theta \in [0, \bar{\theta}]$,

$$Tf(\theta) = \mathbb{E}\left(\int_0^\infty e^{-\left(1+\frac{r}{\lambda}\right)}\left\{f(\theta_t)\,\mathbf{1}_{f(\theta_t)<0\cap\theta_t<\bar{\theta}} + h(\theta_t)\right\}d\theta_t|\theta_0\right).$$

Since $f(z)\,1_{f(z)<0\cap\theta<\bar{\theta}} + h(z)$ is weakly increasing and θ has the FOSD property, Tf is also weakly increasing. Since the space of bounded, continuous and weakly increasing functions is complete, W is also weakly increasing in $\left[0, \bar{\theta}\right]$. This result, together with $h(z)$ being weakly increasing and θ having the FOSD property, imply that W is also weakly increasing for $\theta \geq \bar{\theta}$. □

Now we are ready to prove the main result,

Proposition. *The unique piecewise continuous optimal strategy features a threshold θ^* such that for $\theta < \theta^*$ not exporting is optimal while for $\theta \geq \theta^*$ exporting is optimal.*

Proof. Suppose $W(0) > 0$. Then, since W is weakly increasing, exporting is optimal $\forall\theta$, i.e. $\theta^* = 0$. Suppose $W(0) < 0$. Since W is continuous, weakly increasing and satisfies $W(\bar{\theta}) > 0$, there exists θ^* such that not exporting is optimal $\forall\theta < \theta^*$ ($W(\theta) < 0$), $W(\theta^*) = 0$, and exporting is optimal $\forall\theta > \theta^*$ ($W(\theta) \geq 0$). □

Finally, note that in the particular case discussed in the paper, $\bar{\theta} = \frac{F}{\kappa}$ and, as long as $\alpha < \infty$, $\mathbb{E}_\psi V_e(\frac{F}{\kappa};\psi) - V_i(\frac{F}{\kappa}) > 0$. It follows that $\theta^* < \frac{F}{\kappa}$ or, equivalently, $\tilde{\theta}^* < 1$.

D.3 Derivation of the threshold equation (5)

In the GBM case, the HJB equations become

$$r\mathbb{E}_\psi V_e = \pi^{EE}(\theta_t) + (\mu + \frac{1}{2}\sigma^2)\frac{d\mathbb{E}_\psi V_e}{d\theta} + \frac{1}{2}\sigma^2\frac{d^2\mathbb{E}_\psi V_e}{d\theta^2} \tag{D.12}$$

for the experienced firm and

$$(r+\lambda)V_i = \pi_i + \lambda E_\psi V_e + (\mu + \frac{1}{2}\sigma^2)\frac{dV_i}{d\theta} + \frac{1}{2}\sigma^2\frac{d^2V_i}{d\theta^2} \text{ when } \theta > \theta^* \tag{D.13}$$

$$rV_i = (\mu + \frac{1}{2}\sigma^2)\frac{dV_i}{d\theta} + \frac{1}{2}\sigma^2\frac{dV_i}{d\theta} \text{ when } \theta < \theta^* \tag{D.14}$$

for the inexperienced firm. Define $\Delta V \equiv E_\psi(V_e) - V_i$. Subtracting (D.13) and (D.14) from (D.12) yields

$$(r+\lambda)\Delta V = \pi^{EE}(\theta) - \pi_i + (\mu + \frac{1}{2}\sigma^2)\frac{d\Delta V}{d\theta} + \frac{1}{2}\sigma^2\frac{d^2\Delta V}{d\theta} \text{ when } \theta > \theta^* \tag{D.15}$$

$$r\Delta V = \pi^{EE}(\theta) + (\mu + \frac{1}{2}\sigma^2)\frac{d\Delta V}{d\theta} + \frac{1}{2}\sigma^2\frac{d^2\Delta V}{d\theta} \text{ when } \theta < \theta^* \tag{D.16}$$

When $\theta > \theta^*$, the solution to (D.15) is given by[45]

$$\Delta V(\theta) = \frac{1}{\tilde{J}}\left[\int_\theta^\infty \left(\frac{\theta}{z}\right)^{\tilde{\beta}_1}\left(\pi^{EE}(z) - \pi_i(z)\right)\frac{dz}{z} + \int_{\theta^*}^\theta \left(\frac{\theta}{z}\right)^{\tilde{\beta}_2}\left(\pi^{EE}(z) - \pi_i(z)\right)\frac{dz}{z}\right] + C_{1U}\theta^{\tilde{\beta}_1} + C_{2U}\theta^{\tilde{\beta}_2}$$

where

$$\tilde{J} = \sqrt{\mu^2 + 2(r+\lambda)\sigma^2} \geq |\mu|$$

$$\tilde{\beta}_1 = \frac{-\mu + \tilde{J}}{\sigma^2} > 1$$

$$\tilde{\beta}_2 = \frac{-\mu - \tilde{J}}{\sigma^2} < 0$$

[45] See formula 5.24. in Stokey (2008).

and C_{1U} and C_{2U} are unknown constants. Using the transversality condition, $C_{1U} = 0$.

Note the derivative wrt θ is

$$\frac{d\Delta V}{d\theta} = \frac{1}{\theta}\begin{bmatrix} \tilde{\beta}_1 \frac{1}{\tilde{J}} \int_\theta^\infty \left(\frac{\theta}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} \\ +\tilde{\beta}_2 \frac{1}{\tilde{J}} \int_{\theta^*}^\theta \left(\frac{\theta}{z}\right)^{\tilde{\beta}_2} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} \\ +\tilde{\beta}_2 C_{2U} \theta^{\tilde{\beta}_2} \end{bmatrix}$$

When $\theta < \theta^*$, the solution to (D.16) is given by

$$\Delta V(\theta) = \frac{1}{J}\left[\int_\theta^{\theta^*} \left(\frac{\theta}{z}\right)^{\beta_1} \pi^{EE}(z) \frac{dz}{z} + \int_0^\theta \left(\frac{\theta}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z}\right] + C_{1D}\theta^{\beta_1} + C_{2D}\theta^{\beta_2}$$

where

$$\begin{aligned} J &= \sqrt{\mu^2 + 2r\sigma^2} \geq |\mu| \\ \beta_1 &= \frac{-\mu + J}{\sigma^2} > 1 \\ \beta_2 &= \frac{-\mu - J}{\sigma^2} < 0 \end{aligned}$$

and C_{1D} and C_{2D} are unknown constants. Using the initial condition $\Delta V(0) = 0$, $C_{2D} = 0$.

Note the derivative wrt θ

$$\frac{d\Delta V}{d\theta} = \frac{1}{J}\frac{1}{\theta}\begin{bmatrix} \beta_1 \int_\theta^{\theta^*} \left(\frac{\theta}{z}\right)^{\beta_1} \pi^{EE}(z) \frac{dz}{z} \\ +\beta_2 \int_0^\theta \left(\frac{\theta}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} \\ +\beta_1 C_{1D}\theta^{\beta_1} \end{bmatrix}$$

We have three unknowns, C_{1D}, C_{2U} and θ^*. Using the fact that ΔV is C^1 at θ^*,

$$\begin{aligned} \frac{1}{\tilde{J}}\left[\int_{\theta^*}^\infty \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z}\right] + C_{2U}\theta^{*\tilde{\beta}_2} &= \frac{1}{J}\left[\int_0^{\theta^*} \left(\frac{\theta^*}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z}\right] \\ &\quad + C_{1D}\theta^{*\beta_1} \\ \frac{1}{\tilde{J}}\left[\tilde{\beta}_1 \int_{\theta^*}^\infty \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z}\right] + \tilde{\beta}_2 C_{2U}\theta^{*\tilde{\beta}_2} &= \frac{1}{J}\left[\beta_2 \int_0^{\theta^*} \left(\frac{\theta^*}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z}\right] \\ &\quad + \beta_1 C_{1D}\theta^{*\beta_1}. \end{aligned}$$

Next, multiply the first equation by β_1 and subtract the second equation to obtain,

$$\begin{aligned} &\left(\frac{\beta_1 - \tilde{\beta}_1}{\tilde{J}}\right) \int_{\theta^*}^\infty \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} \\ &\qquad + \left(\beta_1 - \tilde{\beta}_2\right) C_{2U}\theta^{*\tilde{\beta}_2} = \left(\frac{\beta_1 - \beta_2}{J}\right) \int_0^{\theta^*} \left(\frac{\theta^*}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} \end{aligned}$$

Rearranging,

$$C_{2U} = \frac{\theta^{*-\tilde{\beta}_2}}{\beta_1 - \tilde{\beta}_2}\Bigg\{ \left(\frac{\beta_1 - \beta_2}{J}\right) \int_0^{\theta^*} \left(\frac{\theta^*}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} + \left(\frac{\tilde{\beta}_1 - \beta_1}{\tilde{J}}\right) \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} \Bigg\} \tag{D.17}$$

Since $\pi^{EE} - \pi_i \geq 0$ and $\tilde{\beta}_1 \geq \beta_1$, it follows that $C_{2U} \geq 0$. Next, multiply the first equation by $\tilde{\beta}_2$ and subtract the second equation to obtain,

$$\left(\frac{\tilde{\beta}_2 - \tilde{\beta}_1}{\tilde{J}}\right) \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} = \left(\frac{\tilde{\beta}_2 - \beta_2}{J}\right) \int_0^{\theta^*} \left(\frac{\theta^*}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} + \left(\tilde{\beta}_2 - \beta_1\right) C_{1D} \theta^{\beta_1}$$

Rearranging,

$$C_{1D} = \frac{\theta^{*-\beta_1}}{\beta_1 - \tilde{\beta}_2}\Bigg\{ \left(\frac{\tilde{\beta}_1 - \tilde{\beta}_2}{\tilde{J}}\right) \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} + \left(\frac{\tilde{\beta}_2 - \beta_2}{J}\right) \int_0^{\theta^*} \left(\frac{\theta^*}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} \Bigg\} \tag{D.18}$$

The remaining equation is the fact that, by continuity, at the threshold the firm is indifferent between exporting and not exporting, i.e. $\pi_i(\theta^*) + \lambda \Delta V(\theta^*) = 0$,

$$\pi_i(\theta^*) + \frac{1}{\tilde{J}}\lambda \left[\int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} + C_{2U} \theta^{*\tilde{\beta}_2} \right] = 0$$

Substituting in (D.17),

$$\pi_i(\theta^*) + \lambda \left[\begin{array}{c} \frac{1}{\tilde{J}} \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} + \left(\frac{1}{J}\right) \left(\frac{\beta_1 - \beta_2}{\beta_1 - \tilde{\beta}_2}\right) \int_0^{\theta^*} \left(\frac{\theta^*}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} \\ + \left(\frac{1}{\tilde{J}}\right) \left(\frac{\tilde{\beta}_1 - \beta_1}{\beta_1 - \tilde{\beta}_2}\right) \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} \end{array} \right] = 0$$

Simplifying,

$$\pi_i(\theta^*) + \frac{\lambda}{\beta_1 - \tilde{\beta}_2} \left[\begin{array}{c} \left(\tilde{\beta}_1 - \tilde{\beta}_2\right) \frac{1}{\tilde{J}} \int_{\theta^*}^{\infty} \left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1} \left(\pi^{EE}(z) - \pi_i(z)\right) \frac{dz}{z} \\ + \frac{1}{J} \left(\beta_1 - \beta_2\right) \int_0^{\theta^*} \left(\frac{\theta^*}{z}\right)^{\beta_2} \pi^{EE}(z) \frac{dz}{z} \end{array} \right] = 0. \tag{D.19}$$

Next, note

$$\begin{aligned}
\beta_1 - \beta_2 &= \frac{2J}{\sigma^2} \\
\tilde{\beta}_1 - \tilde{\beta}_2 &= \frac{2\tilde{J}}{\sigma^2} \\
\beta_1 - \tilde{\beta}_2 &= \frac{J + \tilde{J}}{\sigma^2}
\end{aligned}$$

Thus,

$$\pi_i\left(\theta^*\right) + \lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\int_{\theta^*}^{\infty}\left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1}\left(\pi^{EE}\left(z\right) - \pi_i\left(z\right)\right)\frac{dz}{z} + \int_0^{\theta^*}\left(\frac{\theta^*}{z}\right)^{\beta_2}\pi^{EE}\left(z\right)\frac{dz}{z}\right] = 0.$$

As suggested in the main body, this equation shows that the model boils down to one equation in one unknown even if ψ is not multiplicative. In our baseline model, $\pi^{EE} = \mathbb{E}_\psi\left[\max\left\{\psi\frac{\kappa\theta}{F} - 1, 0\right\}\right]$ and $\pi_i = \kappa\theta - F$. Replacing,

$$\begin{aligned}
\kappa\theta - F + \lambda\left(\frac{2}{J+\tilde{J}}\right)\Bigg\{\int_{\theta^*}^{\infty}\left(\frac{\theta^*}{z}\right)^{\tilde{\beta}_1}\left(\mathbb{E}_\psi\left(\max\left\{\psi\kappa z - F, 0\right\}\right) - \left(\kappa z - 1\right)\right)\frac{dz}{z} \\
+ \int_0^{\theta^*}\left(\frac{\theta^*}{z}\right)^{\beta_2}\mathbb{E}_\psi\left(\max\left\{\psi\kappa z - F, 0\right\}\right)\frac{dz}{z}\Bigg\} = 0.
\end{aligned}$$

In terms of $\tilde{\theta}$ and redefining $z = \frac{\kappa z}{F}$:

$$\begin{aligned}
\tilde{\theta} - 1 + \lambda\left(\frac{2}{J+\tilde{J}}\right)\Bigg\{\int_{\tilde{\theta}^*}^{\infty}\left(\frac{\tilde{\theta}^*}{z}\right)^{\tilde{\beta}_1}\left(\mathbb{E}_\psi\left(\max\left\{\psi z - 1, 0\right\}\right) - \left(z - 1\right)\right)\frac{dz}{z} \\
+ \int_0^{\tilde{\theta}^*}\left(\frac{\tilde{\theta}^*}{z}\right)^{\beta_2}\mathbb{E}_\psi\left(\max\left\{\psi z - 1, 0\right\}\right)\frac{dz}{z}\Bigg\} = 0.
\end{aligned}$$

D.4 Proof of Proposition 3

First, let us compute $\mathbb{E}_\psi(\max\{\psi z - 1, 0\})$. When $z > \psi_m^{-1}$,

$$\mathbb{E}_\psi(\max(\psi z - 1, 0) = (\frac{\alpha}{\alpha - 1})\psi_m z - 1, \tag{D.20}$$

which is decreasing in α. When $z < \psi_m^{-1}$,

$$\mathbb{E}_\psi(\max(\psi z - 1, 0) = (\frac{1}{\alpha - 1})\psi_m^\alpha z^\alpha, \tag{D.21}$$

which is decreasing in α since $\ln\left(\psi_m^\alpha z^\alpha\right) < 0$ in this region. Thus, $\mathbb{E}_\psi \max\{\psi z - 1, 0\}$ decreases with α $\forall z$ and, thus, the LHS of equation (5) decreases with α.

Next, define $m = \frac{z}{\tilde{\theta}^*}$ and rewrite equation (5) as

$$\tilde{\theta}^* - 1 + \lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c} \int_1^\infty m^{-\tilde{\beta}_1}\left(E_\psi\left(\max\left(\psi\tilde{\theta}^* m - 1, 0\right)\right) - \left(\tilde{\theta} m - 1\right)\right)\frac{dm}{m} \\ + \int_0^1 m^{-\beta_2} E_\psi\left(\max\left(\psi\tilde{\theta}^* m - 1, 0\right)\right)\frac{dm}{m} \end{array}\right] = 0 \quad \text{(D.22)}$$

Solving the second integral in the first line of the bracket,

$$\begin{array}{r} \tilde{\theta}^*\Big(1 - \dfrac{2\lambda}{(J+\tilde{J})(\tilde{\beta}_1 - 1)}\Big) - \Big(1 - \dfrac{2\lambda}{(J+\tilde{J})\tilde{\beta}_1}\Big) \\ +\lambda\left(\dfrac{2}{J+\tilde{J}}\right)\left[\begin{array}{c} \int_1^\infty m^{-\tilde{\beta}_1} E_\psi\left(\max\left(\psi\tilde{\theta}^* m - 1, 0\right)\right))\frac{dm}{m} \\ + \int_0^1 m^{-\beta_2} E_\psi\left(\max\left(\psi\tilde{\theta}^* m - 1, 0\right)\right)\frac{dm}{m} \end{array}\right] = 0 \end{array}$$

Since $1 - \lambda\frac{2}{J+\tilde{J}}\frac{1}{\tilde{\beta}-1} \geq 0$, the LHS decreases with $\tilde{\theta}^*$. Thus, by the implicit function theorem, $\tilde{\theta}^*$ increases with α.

D.5 Proof of Proposition 4

Define $\hat{\theta} = \psi_m\tilde{\theta}$ and $\tilde{\psi} = \frac{\psi}{\psi_m}$ and rewrite Equation (5),

$$\frac{1}{\psi_m}\hat{\theta} - 1 + \lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c} \int_{\frac{1}{\psi_m}\hat{\theta}^*}^{:\infty}\left(\frac{\hat{\theta}^*}{\psi_m z}\right)^{\tilde{\beta}_1}\left(E\max\left\{\psi_m\tilde{\psi} z - 1\right\} - (z-1)\right)\frac{dz}{z} \\ + \int_0^{\frac{1}{\psi_m}\hat{\theta}^*}\left(\frac{\hat{\theta}^*}{\psi_m z}\right)^{\beta_2} E\max\left\{\psi_m\tilde{\psi} z - 1\right\}\frac{dz}{z} \end{array}\right] = 0$$

Let $\hat{z} \equiv \psi_m z$. Then,

$$\begin{aligned} &\frac{1}{\psi_m}\hat{\theta} - 1 \\ +\lambda\left(\frac{2}{J+\tilde{J}}\right)&\left[\begin{array}{c} \int_{\hat{\theta}^*}^{:\infty}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\tilde{\beta}_1}\left(E\max\left\{\tilde{\psi}\hat{z} - 1, 0\right\} - \frac{1}{\psi_m}\hat{z} + 1\right)\frac{d\hat{z}}{\hat{z}} \\ + \int_0^{\hat{\theta}^*}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\beta_2} E\max\left\{\tilde{\psi}\hat{z} - 1\right\}\frac{d\hat{z}}{\hat{z}} \end{array}\right] \quad = \quad 0 \\ &\frac{1}{\psi_m}\left(\hat{\theta} - \lambda\left(\frac{2}{J+\tilde{J}}\right)\int_{\hat{\theta}^*}^{:\infty}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\tilde{\beta}_1} d\hat{z}\right) - 1 \\ +\lambda\left(\frac{2}{J+\tilde{J}}\right)&\left[\begin{array}{c} \int_{\hat{\theta}^*}^{:\infty}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\tilde{\beta}_1}\left(E\max\left\{\tilde{\psi}\hat{z} - 1, 0\right\} + 1\right)\frac{d\hat{z}}{\hat{z}} \\ + \int_0^{\hat{\theta}^*}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\beta_2} E\max\left\{\tilde{\psi}\hat{z} - 1\right\}\frac{d\hat{z}}{\hat{z}} \end{array}\right] \quad = \quad 0 \\ &\frac{1}{\psi_m}\hat{\theta}\left(1 - \lambda\frac{2}{J+\tilde{J}}\frac{1}{\tilde{\beta}_1 - 1}\right) - 1 \\ +\lambda\left(\frac{2}{J+\tilde{J}}\right)&\left[\begin{array}{c} \int_{\hat{\theta}^*}^{:\infty}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\tilde{\beta}_1}\left(E\max\left\{\tilde{\psi}\hat{z} - 1, 0\right\} + 1\right)\frac{d\hat{z}}{\hat{z}} \\ + \int_0^{\hat{\theta}^*}\left(\frac{\hat{\theta}^*}{\hat{z}}\right)^{\beta_2} E\max\left\{\tilde{\psi}\hat{z} - 1\right\}\frac{d\hat{z}}{\hat{z}} \end{array}\right] \quad = \quad 0 \end{aligned}$$

Since $1 - \lambda\frac{2}{J+\tilde{J}}\frac{1}{\tilde{\beta}-1} \geq 0$, the LHS decreases with ψ_m.

Changing the dummy of integration to $m = \frac{z}{\hat{\theta}^*}$,

$$\frac{1}{\psi_m}\hat{\theta}\left(1 - \lambda\frac{2}{J+\tilde{J}}\frac{1}{\tilde{\beta}_1 - 1}\right) - 1 + \lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c} \int_1^{:\infty} m^{-\tilde{\beta}_1}\left(E\max\left\{\tilde{\psi}m\hat{\theta}^* - 1, 0\right\} + 1\right)\frac{dm}{m} \\ + \int_0^1 m^{-\beta_2} E\max\left\{\tilde{\psi}m\hat{\theta}^* - 1\right\}\frac{dm}{m} \end{array}\right] = 0$$

The first derivative wrt $\hat{\theta}^*$ yields

$$\frac{1}{\psi_m}\left(1 - \lambda\frac{2}{J+\tilde{J}}\frac{1}{\tilde{\beta}_1 - 1}\right) + \lambda\left(\frac{2}{J+\tilde{J}}\right)\left[\begin{array}{c} \int_1^{\infty} m^{-\tilde{\beta}_1+1}\frac{dE\left[\max\left\{\psi m\tilde{\theta}^* - 1\right\}\right]}{dm\tilde{\theta}^*}\frac{dm}{m} \\ + \int_0^1 m^{-\beta_2+1}\frac{dE\left[\max\left\{\psi m\tilde{\theta}^* - 1\right\}\right]}{dm\tilde{\theta}^*}\frac{dm}{m} \end{array}\right] > 0.$$

Hence, the LHS increases with $\hat{\theta}^*$. Thus, by the implicit function theorem, $\frac{d\hat{\theta}^*}{d\psi_m} > 0$.

E Estimation details

E.1 SMM estimator

The firms in our sample that are used for estimation may enter a market j twice: once as first-time entrants and once as re-entrants. For each entry, we let $y_{ij\tau r} \in \{0, 1\}$ denote the export participation decision τ years after entry of firm i, with the subindex r denoting whether it is a first-time entrant ($r = 0$) or a re-entrant ($r = 1$). Recall that years are redefined according to the time of the first shipment to avoid partial-year effects.

Our SMM estimator uses ten moments. The first five moments are survival probabilities of first-time entrants:

$$\frac{1}{N}\sum_{i=1}^{N}\Big\{\frac{1}{J_i}\sum_{j=1}^{J_i}\{y^{obs}_{ij\tau 0} - \frac{1}{S}\sum_{s=1}^{S} y^{s}_{ij\tau 0}(\varphi)\}\Big\} = 0 \qquad \text{for} \qquad \tau = 1, \ldots, 5. \tag{E.1}$$

where $\varphi = \{\mu, \sigma, \lambda, \alpha\}$ is the vector of model parameters, $y^{obs}_{ij\tau 0}$ denotes the observed export-participation decision, $y^{s}_{ij\tau 0}(\varphi)$ is the analogous model-implied export participation decision, N is the number of firms that are first-time entrants at least in one market, J_i the number of such entry markets for firm i, and S is the number of model simulations.

The last five moments are survival probabilities of re-entrants,

$$\frac{1}{N}\sum_{i=1}^{N}\Big\{\frac{1}{J_i}\sum_{j=1}^{J_i}\{\sum_{r=0,1}(y^{obs}_{ij\tau r} - \frac{1}{S}\sum_{s=1}^{S} y^{s}_{ij\tau r}(\theta, z_{ij}))\mathbf{1}_{r=1}\}\Big\} = 0 \qquad \text{for} \qquad \tau = 1, \ldots, 5. \tag{E.2}$$

where $\mathbf{1}_{r=1}$ is an indicator function for the event $r = 1$, so that only re-entrant observations contribute to these moments and z_{ij} is the amount of time that passed between the date of the first entry and the date of the first re-entry. Unlike first-time entrants, who all enter as inexperienced firms (equation 8), re-entrants may enter experienced or inexperienced (equation 9). The probability of being each type of re-entrant depends on the age of the exporter: if a firm spent a long time active in the market, then the likelihood of being experienced when it re-enters it increases. Importantly, the share of experienced re-entrants affects the expected re-entry survival rate. Given that the sample covers the period 1997-2008 and that we only consider re-entrants who we also observe as first-time entrants, the latest year in which the firm could re-enter is year 6 in the export experience (the firm should have exited and then re-entered again with five years left to study survival). The latest possible re-entrant with five years to study survival is a firm that enters on January 1st 1997, exits in 2001, and re-enters on December 31st 2002 (year 6). [46] In other words, our sample is biased towards young, inexperienced re-entrants. To capture this effect, we write our re-entry survival moment as the expected survival rate for re-entrants conditional on the firm-market-specific "age" z_{ij} and then sum over the observed z_{ij}. We define z_{ij} in years for computational tractability. More

[46]We could also include firms that, having entered on January 1st 1997, exited in 2002 and re-entered on January 1st 2003, but we do not see such a firm in our sample.

precisely, we create three groups: firms with a re-entry shipment between 2 and 3 years after the first-entry shipment, between 3 and 4 years, and more than 4 years later (up to year 6).

Let $m_k(\varphi)$, with $k = 1, \ldots, 10$, denote the ten moments above and $m(\varphi)$ a vector with these ten moments. Our SMM estimator chooses φ to minimize $m(\varphi)'Wm(\varphi)$. Since all our moments are survival probabilities, we choose an identity matrix as the weighting matrix W.

Furthermore, given that the objective function is non-smooth, we took a three-step approach. First, we fixed μ and estimated the remaining parameters: μ was fixed alternatively at 0, -0.025, -0.05, -0.075, -0.1, -0.15 and -0.2. The model performance clearly decreased for values larger than -0.1. Thus, in a second step, we estimated the model using the genetic algorithm *ga* in MATLAB with a population size of 1000 within a narrower set of parameters guided by the best points in the previous grid (μ between 0 and -0.1). Finally, we refined the solution with a local optimizer, fminsearch.

E.2 Simulation details

Our goal is to simulate equations (8) and (9). Thus, there are three objects that we need to simulate: (i) the survival rate of an inexperienced firm, (ii) the survival rate of an experienced firm, and (iii) the probability of being an experienced re-entrant for each of the three possible values of z_{ij}. We simulate $S = 200,000$ firms for $T = 6$ years with a time interval of $dt = 0.001$.[47] Since all firms and markets are identical (except for κ and F, but those are irrelevant for survival, see Proposition 2), we use the same simulations for all firm-markets. Since the interval is of size dt, there are $1/dt$ "instants" per year. In the data, we define firm-market-specific years according to the time of first entry. Accordingly, in the model, instants between $\tau/dt + 1$ and $(\tau + 1)/dt$ correspond to year τ of the firm's export experience (letting 0 denote the entry year). In each simulation, there is a random draw for the GBM process, i.e. $T/dt = 6000$ random draws of dZ_t - one per instant, a random draw for whether the firm becomes experienced in each instant if it decides to export - also one per instant so 6000 additional draws, and a random draw of ψ.

Consider first the survival rate of inexperienced firms. Since the GBM is continuous, firms enter exactly at the threshold, $\tilde{\theta}_0 = \tilde{\theta}^*$. Using this result and the random draws of the GBM, we construct the path for $\tilde{\theta}_t$. Whenever $\tilde{\theta}_t \geq \tilde{\theta}^*$, we check whether the firm becomes experienced according to the corresponding random draw. If so, we modify the firm's (normalized) operating profits from the next instant onwards from $\tilde{\theta}_t$ to $\psi\tilde{\theta}_t$. While inexperienced, the firm is active in any given instant if $\tilde{\theta}_t \geq \tilde{\theta}^*$. Once it becomes experienced, which is an absorbing state, it is only active if $\psi\tilde{\theta}_t \geq 1$. If the firm is active in any instant $t \in [\tau/dt + 1, (\tau + 1)/dt]$, then the firm is active in year τ. The firm is always active by definition in the first year ($\tau = 0$). The subsequent five years $\tau = 1, \ldots, 5$ are used to construct the required survival probabilities of inexperienced firms, which are also the survival probabilities of first-time entrants (the first five moments).

Next, we compute the survival rate of experienced firms. These firms also enter exactly at their

[47] In Section I, we need to simulate more years since firms do not enter exactly at the threshold.

relevant threshold, i.e. $\psi\tilde{\theta}_0 = 1$. Since entry and exit thresholds coincide for experienced firms, and the GBM is memoryless, we do not need to keep track of ψ to compute this survival rate. That is, we start the process at any value, e.g. $\tilde{\theta} = 1$, we construct the path for $\tilde{\theta}_t$ using the random draws of the GBM, and then we check in every instant whether the process is above the initial value, e.g. whether $\tilde{\theta}_t \geq 1$. If the firm is active in any instant $t \in [\tau/dt + 1, (\tau + 1)/dt]$, then the firm is active in year τ. The fact that the GBM is memoryless implies that this computation is independent of the chosen value to start the process (e.g. $\tilde{\theta}_0 = 1$).

Finally, we need to compute the share of firms that enter experienced vs. inexperienced for each of the z_{ij} values. To do so, for each of the $S = 200,000$ firms that we simulate starting as inexperienced firms, we check whether they become re-entrants (only for the first time, as in the data).[48] If so, we keep track of their experience status at the moment of re-entry, we check the date of the first shipment as a re-entrant and using this we compute the amount of time that has passed since the first shipment of the first entry. Using this, we classify the re-entry into one of the three possible values of z_{ij}. Then, we compute the share of the firms in each category of z_{ij} that are experienced. Armed with the three pieces, we can calculate the predicted re-entry probability for each z_{ij} using equation (9).

[48]Note that since the maximum value of z_{ij} is year 6, we do not need to simulate extra years.

F Sunk cost model

There are two types of firms: "experienced" firms, who have entered the market at least once in the past, and "inexperienced" firms, who have not. The difference between these firms is that experienced firms pay a lower sunk cost to enter the market: $0 \leq S_e \leq S_i$. We shut down the experimentation mechanism by setting $\lambda = 0$. We assume that all firms have the same ratio of sunk to fixed costs, which allows us to preserve a large degree of firm heterogeneity that does not affect survival (Albornoz et al., 2016).

Experienced firms The analysis in this region is the same as the model in Appendix 2 of (Albornoz et al., 2016), which we repeat here for convenience. Within this region, there are two subregions. Firms with $\tilde{\theta} > \underline{\tilde{\theta}}_e$, export if they exported the previous instant. We call these firms "active" exporters and denote their value function with a subindex 1. Firms with $\tilde{\theta} < \overline{\tilde{\theta}}_e$ do not export if they did not export the previous instant. We call these firms "inactive" exporters and denote their value function with a subindex 0. As we will verify later, $\underline{\tilde{\theta}}_e \leq \overline{\tilde{\theta}}_e$, strictly so if $S_e > 0$.

Inactive exporters do not generate any income flow in market k while they are outside the market. Their value function satisfies the HJB equation

$$rV_{0e}(\tilde{\theta})dt = \mathbb{E}(dV_{0e}(\tilde{\theta})).$$

Applying Ito's Lemma,

$$rV_{0e}(\tilde{\theta})dt = (\mu + \frac{1}{2}\sigma^2)\frac{dV_{0e}(\tilde{\theta})}{d\tilde{\theta}} + \frac{1}{2}\sigma^2\frac{d^2V_{0e}(\tilde{\theta})}{d\tilde{\theta}^2}.$$

Guess and verify that the solution is of the form

$$V_{0e}(\tilde{\theta}) = A_{0e}\tilde{\theta}^{\beta}_1 + \tilde{A}_{0e}\tilde{\theta}^{\beta}_2$$

where the roots β_1 and β_2 are given by

$$\beta_{1,2} = -\frac{\mu}{\sigma^2} \pm \sqrt{(\frac{\mu}{\sigma^2})^2 + 2\frac{r}{\sigma^2}}.$$

Using the fact that $\mu + \frac{1}{2}\sigma^2 < r$ (otherwise profits are infinite), one can establish that $\beta_1 > 1$ and $\beta_2 < 0$. Since the value of the firm is zero when $\tilde{\theta} = 0$, $\tilde{A}_{0e} = 0$. Therefore, we obtain

$$V_{0e}(\tilde{\theta}) = A_{0e}\tilde{\theta}^{\beta}_1.$$

Active exporters generate an income flow of $F(\tilde{\theta} - 1)dt$. Their value function satisfies the HJB equation

$$rV_{1e}(\tilde{\theta})dt = F(\tilde{\theta} - 1)dt + \mathbb{E}(dV_{1e}(\tilde{\theta})).$$

Applying Ito's Lemma,

$$rV_{1e}(\tilde{\theta})dt = F(\tilde{\theta}-1)dt + (\mu + \frac{1}{2}\sigma^2)\frac{dV_{1e}(\tilde{\theta})}{d\tilde{\theta}} + \frac{1}{2}\sigma^2\frac{d^2V_{1e}(\tilde{\theta})}{d\tilde{\theta}^2}.$$

Guess and verify that the solution is of the form

$$V_{0e}(\tilde{\theta}) = \tilde{A}_{1e}\tilde{\theta}_1^{\beta} + A_{1e}\tilde{\theta}_2^{\beta} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\tilde{\theta} - \frac{F}{r}$$

where the roots β_1 and β_2 are given by

$$\beta_{1,2} = -\frac{\mu}{\sigma^2} \pm \sqrt{(\frac{\mu}{\sigma^2})^2 + 2\frac{r}{\sigma^2}}.$$

When $\tilde{\theta} \to \infty$, the value of inaction should go to zero and profits should converge to $(\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\tilde{\theta} - \frac{F}{r}$ so $\tilde{A}_{1e} = 0$. Therefore, we obtain

$$V_{1e}(\tilde{\theta}) = A_{1e}\tilde{\theta}_2^{\beta} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\tilde{\theta} - \frac{F}{r}.$$

There are still four unknowns left: $A_{0e}, A_{1e}, \underline{\tilde{\theta}}_e, \overline{\tilde{\theta}}_e$. To find them we use the value-matching and smooth pasting conditions at the thresholds:

$$\begin{aligned} V_{0e}(\overline{\tilde{\theta}}_e) &= V_{1e}(\overline{\tilde{\theta}}_e) - S_e \\ \frac{dV_{0e}(\overline{\tilde{\theta}}_e)}{d\tilde{\theta}} &= \frac{dV_{1e}(\overline{\tilde{\theta}}_e)}{d\tilde{\theta}} \\ V_{0e}(\underline{\tilde{\theta}}_e) &= V_{1e}(\underline{\tilde{\theta}}_e) \\ \frac{dV_{1e}(\underline{\tilde{\theta}}_e)}{d\tilde{\theta}} &= \frac{dV_{0e}(\underline{\tilde{\theta}}_e)}{d\tilde{\theta}} \end{aligned}$$

Plugging in:

$$\begin{aligned} A_{0e}\overline{\tilde{\theta}}_e^{\beta_1} &= A_{1e}\overline{\tilde{\theta}}_e^{\beta_2} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\overline{\tilde{\theta}}_e - \frac{F}{r} - S_e \\ \beta_1 A_{0e}\overline{\tilde{\theta}}_e^{\beta_1-1} &= \beta_2 A_{1e}\overline{\tilde{\theta}}_e^{\beta_2-1} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2}) \\ A_{0e}\underline{\tilde{\theta}}_e^{\beta_1} &= A_{1e}\underline{\tilde{\theta}}_e^{\beta_2} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\underline{\tilde{\theta}}_e - \frac{F}{r} \\ \beta_1 A_{0e}\underline{\tilde{\theta}}_e^{\beta_1-1} &= \beta_2 A_{1e}\underline{\tilde{\theta}}_e^{\beta_2-1} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2}) \end{aligned}$$

Note that in these equations it is immediate that only S_e/F matters. We solve this system of equations numerically.

Inexperienced firms This is very similar, except that the sunk cost is different. Value-matching and smooth-pasting are:

$$V_{0i}(\bar{\tilde{\theta}}_i) = V_{1e}(\bar{\tilde{\theta}}_i) - S_i$$
$$\frac{dV_{0i}(\bar{\tilde{\theta}}_i)}{d\tilde{\theta}} = \frac{dV_{1e}(\bar{\tilde{\theta}}_i)}{d\tilde{\theta}}$$

Plugging in:

$$A_{0i}\bar{\tilde{\theta}}_i^{\beta_1} = A_{1e}\bar{\tilde{\theta}}_i^{\beta_2} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})\bar{\tilde{\theta}}_i - \frac{F}{r} - S_i$$
$$\beta_1 A_{0i}\bar{\tilde{\theta}}_i^{\beta_1-1} = \beta_2 A_{1e}\bar{\tilde{\theta}}_i^{\beta_2-1} + (\frac{F}{r-\mu-\frac{1}{2}\sigma^2})$$

This is a system of two equations in two unknowns (A_{0i} and $\bar{\tilde{\theta}}_i$). It's an easier to solve since we already know the value of becoming an exporter (governed by $A_1 e$), which goes together with becoming experienced in this model. We solve this numerically.

G Survival with non-marginal entry

In the baseline model, all firms are born with θ below the export threshold θ^*. Since profitability follows a diffusion, the exact initial value is irrelevant: all firms that eventually export do so by crossing θ^* continuously, so every first-time entrant is marginal. Here we extend the model to allow a fraction of firms to be "born-global": they draw an initial profitability $\theta_0 \geq \theta^*$ and begin exporting immediately at birth.

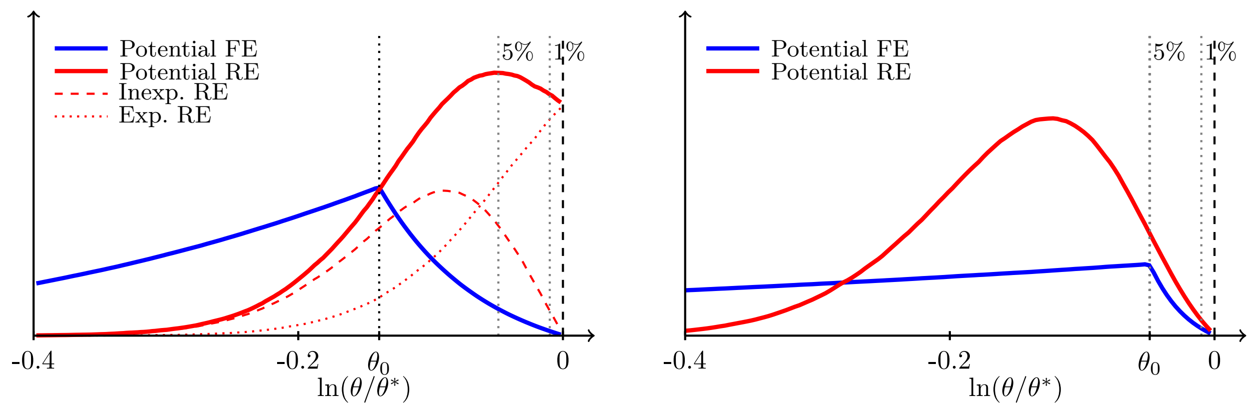
Setup We draw the initial profitability of each firm from a Pareto distribution with location parameter θ_0 and shape parameter α_0:

$$\Pr(\theta \geq x) = \left(\frac{\theta_0}{x}\right)^{\alpha_0}, \quad x \geq \theta_0.$$

The location $\theta_0 \leq \theta^*$ pins down the share of firms that export at some point during their lifetime (ever-exporters), and the shape α_0 pins down the share of those ever-exporters that are born above θ^* (born-global firms). A lower α_0 implies a thicker right tail and more born-global firms. Since neither the ever-export share nor the born-global share is directly observable in our data, we consider a range of values: 10% and 25% for the born-global share of ever-exporters, and 10%, 20%, and 30% for the ever-export share of all firms.

Stationary distributions of potential entrants We simulate the model to stationarity and record the distribution of inactive firms just below θ^*—the pool of potential entrants activated by an increase in profitability. Figure G.1 plots these distributions separately for potential first-time entrants and potential re-entrants. Since σ is not separately identified in the benchmark model, we set $\sigma = 0.043$, matching the baseline estimate. In both models, the density of potential entrants drops to zero as θ approaches θ^* from below, since θ^* is an absorbing barrier: firms that reach it begin exporting and leave the inactive pool. In the baseline model, the density of potential re-entrants is flatter near θ^*: firms that draw a low ψ upon learning exit with a discrete jump, scattering them at various distances below the threshold rather than piling up just beneath it. Re-entrants are further decomposed into inexperienced and experienced subgroups. The gray dotted lines mark the post-shock thresholds for 5% and 1% increases in profitability; firms between these lines and θ^* are the marginal entrants activated by the shock, whose survival we track below.

Steady-state survival Table G.1 reports one-year survival rates in steady state across all calibrations. The first row reports the estimation baseline without born-global firms: the gap between re-entrant and first-time entrant survival is 14.2 percentage points in the baseline model and zero in the benchmark. Adding born-global firms raises pooled first-time entrant survival, since some entrants start above θ^*, but the RE–FE gap remains large and positive across all baseline calibrations. In the benchmark model, born-global firms survive at higher rates than re-entrants—since without



(a) Baseline ($\lambda > 0$)

(b) Benchmark ($\lambda = 0$)

Figure G.1: Stationary distributions of potential entrants near θ^*

Notes: Simulated stationary densities of inactive firms just below the export threshold θ^* (vertical dashed line). Blue: potential first-time entrants. Red: potential re-entrants (solid = total; in the baseline panel, dashed = inexperienced, dotted = experienced). The dotted vertical line marks the location parameter θ_0. Gray dotted lines mark the post-shock thresholds for 5% and 1% profitability increases. Shown for 20% ever-export share, no born-global firms.

experimentation ($\lambda = 0$) re-entrants have no learning advantage—so any positive born-global share reverses fact 2.

Response to shocks Table G.2 reports the survival of first-time entrants and re-entrants following permanent increases in profitability of 5% and 1% (for reference, the estimated annual standard deviation of profitability is $\sigma = 4.3\%$). To isolate the role of the jump in profitability, we report results without born-global firms: all first-time entrants are marginal, entering at θ^*.

A notable feature of the baseline model is that first-time entrant survival after the shock is *below* its steady-state value. This reflects a "learning death" effect: firms activated by the shock start just above θ^*, where learning shocks arrive at rate λ. At $\theta \approx \theta^*$, approximately $1 - (\theta^*)^\alpha \approx 87\%$ of learning draws yield a ψ too low for the firm to survive as experienced. Because starting above θ^* increases exposure to these mostly lethal learning shocks, first-time entrant survival is a U-shaped function of the initial distance from the threshold. Re-entrant survival, by contrast, exceeds its steady-state value after the shock, because the experienced component—which faces no learning risk—benefits unambiguously from starting above the exit threshold.

In the baseline model, the re-entrant survival advantage is large and robust for both shock sizes. In the benchmark model, the gap is essentially zero for both shock sizes.

Table G.1: Steady-state survival with non-marginal entry

	Baseline ($\lambda > 0$)			Benchmark ($\lambda = 0$)		
	FE	RE	Gap	FE	RE	Gap
No born-to-export	30.0	44.2	14.2	41.6	41.6	0.0
Born-to-export share = 10%						
$X_2 = 10\%$	31.5	46.1	14.6	43.3	41.6	-1.7
$X_2 = 20\%$	31.0	45.8	14.8	43.2	41.6	-1.6
$X_2 = 30\%$	30.7	45.6	14.9	43.0	41.6	-1.3
Born-to-export share = 25%						
$X_2 = 10\%$	36.2	47.7	11.5	48.0	41.6	-6.3
$X_2 = 20\%$	35.2	47.7	12.5	47.4	41.6	-5.8
$X_2 = 30\%$	34.2	47.7	13.5	46.8	41.6	-5.2

Notes: One-year survival probabilities (%). FE = pooled first-time entrants (marginal + born-to-export). RE = first-time re-entrants, weighted across cohorts (2–3, 3–4, 4–6 years since first entry) using data counts. Gap = RE − FE. X_2 = ever-export share. The "no born-to-export" row uses the baseline estimation values.

Table G.2: Survival after a permanent shock

	FE		RE	
Shock	t=1	t=5	t=1	t=5
Panel A: Baseline model ($\lambda > 0$)				
5%	28.8	19.8	49.5	32.4
1%	29.0	17.8	45.1	28.3
Panel B: Benchmark model ($\lambda = 0$)				
5%	53.2	11.8	54.1	12.0
1%	44.1	9.7	44.2	9.6

Notes: FE = first-time entrants (entering at θ^*); RE = first-time re-entrants, weighted across cohorts (2–3, 3–4, 4–6 years since first entry) using data counts. Survival probabilities (%) reported at horizons $t = 1$ and $t = 5$ years after a permanent increase in profitability of the indicated size (as a reference, the estimated annual standard deviation of profitability is $\sigma = 4.3\%$). Ever-export share: 20%.

H Alternative estimations

H.1 Targeting conditional survival moments

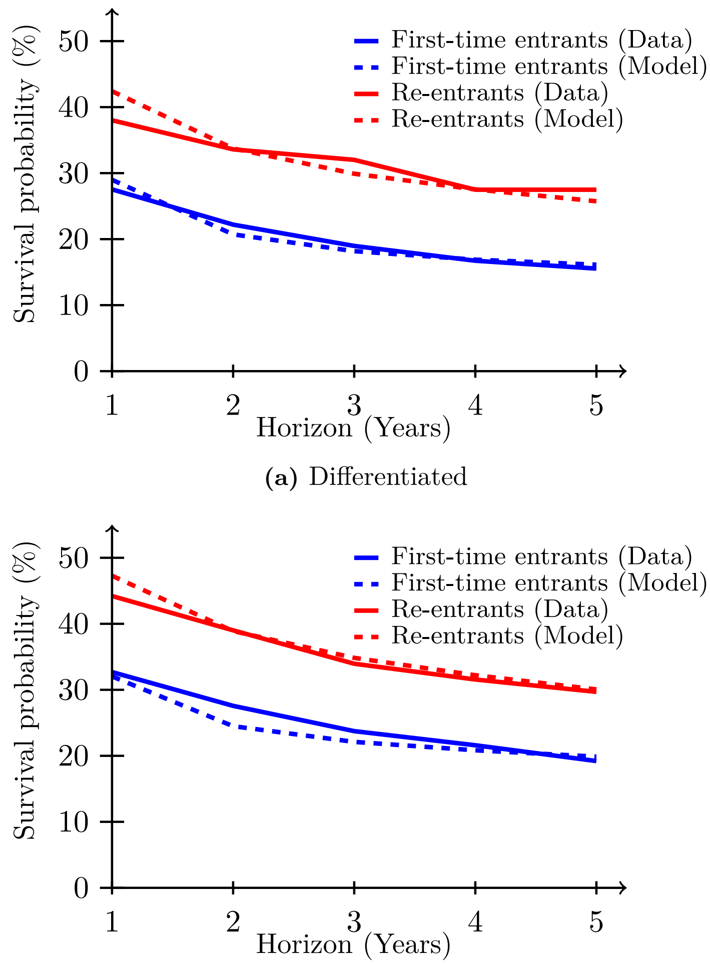
In this appendix, we re-estimate the model by including the four conditional survival moments of Figure 10b in the set of moments to match (in addition to the ten moments of the baseline estimation). Table H.1 shows the results. The model does an excellent job at matching continuous conditional survival probabilities and even improves the fit to the first-time entrant survival profile (fact 1). By contrast, the fit for re-entrants worsens, but it is still very good: the average discrepancy is 2.7 percentage points instead of 1.2. The model overestimates the first-year re-entrant survival rate by more and predicts a profile that is too steep. To understand why, note that this alternative estimation strategy delivers faster learning (i.e. higher $\hat{\lambda}$). This implies that a larger share of re-entrants are experienced, which raises their survival rate (58% of re-entrants are experienced vs 41% in the main estimation). Furthermore, to match better continuous conditional survival probabilities, the estimation picks a more negative $\frac{\hat{\mu}}{\hat{\sigma}}$ (-0.35). This makes the slope of the survival profile steeper, especially for experienced firms and, thus, for re-entrants. Regarding the other moments analyzed in Section 6, these new estimates neither substantially improve nor worsen the model's fit (results available upon request).

H.2 Results by market type

To assess whether the model can also account for the cross-market patterns documented in Section 5, we re-estimate the model separately by market type, holding μ, σ, and λ fixed at their baseline values and allowing only α to vary across groups. Figure H.1 reports the resulting model fit for product-type groups, Figure H.2 does the same for distance groups, and Figure H.3 reports the product-type-by-distance interactions. Overall, the model tracks the level and shape of the survival profiles across groups reasonably well. In particular, the estimates imply lower values of α for differentiated products and for more distant destinations, consistent with the interpretation that these markets are associated with greater uncertainty.

Table H.1: SMM Estimation results: Alternative targets

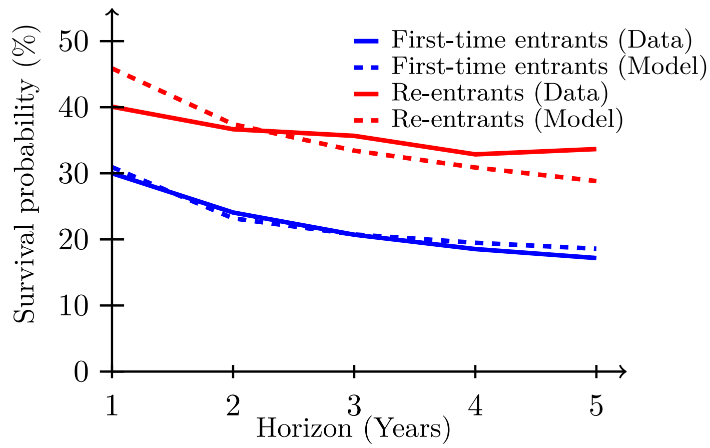
	Fixed parameters	
r	0.1	
ψ_m	1	
	Estimated parameters	
μ	-0.0582	
σ	0.1645	
λ	4.456	
α	4.622	
	Survival probabilities	
	Panel A: First-time entrants	
	Model	Data
Year 1	0.298	0.294
Year 2	0.233	0.242
Year 3	0.203	0.208
Year 4	0.183	0.185
Year 5	0.166	0.169
	Panel B: Re-entrants	
Year 1	0.465	0.405
Year 2	0.372	0.357
Year 3	0.317	0.329
Year 4	0.279	0.290
Year 5	0.247	0.282
	Panel C: Conditional survival	
Year 2	0.606	0.629
Year 3	0.731	0.718
Year 4	0.805	0.784
Year 5	0.830	0.825



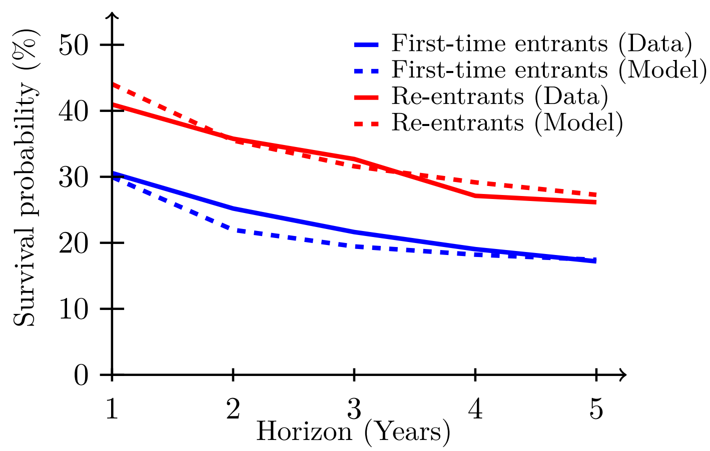
(a) Differentiated

(b) Homogeneous

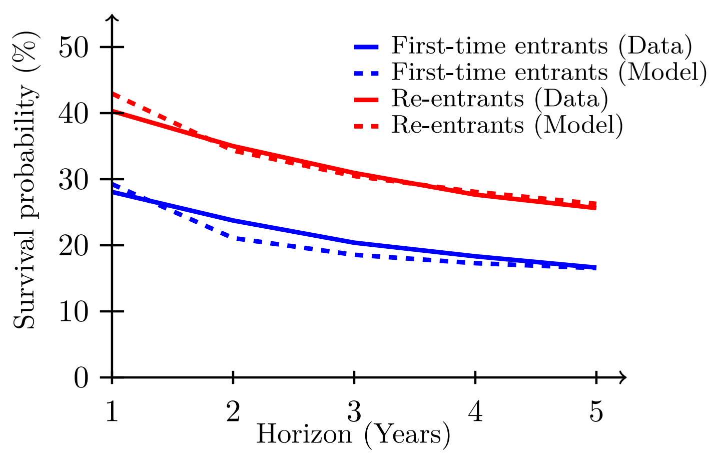
Figure H.1: Survival profiles by product type



(a) Short distance



(b) Medium distance



(c) Long distance

Figure H.2: Survival profiles by distance group

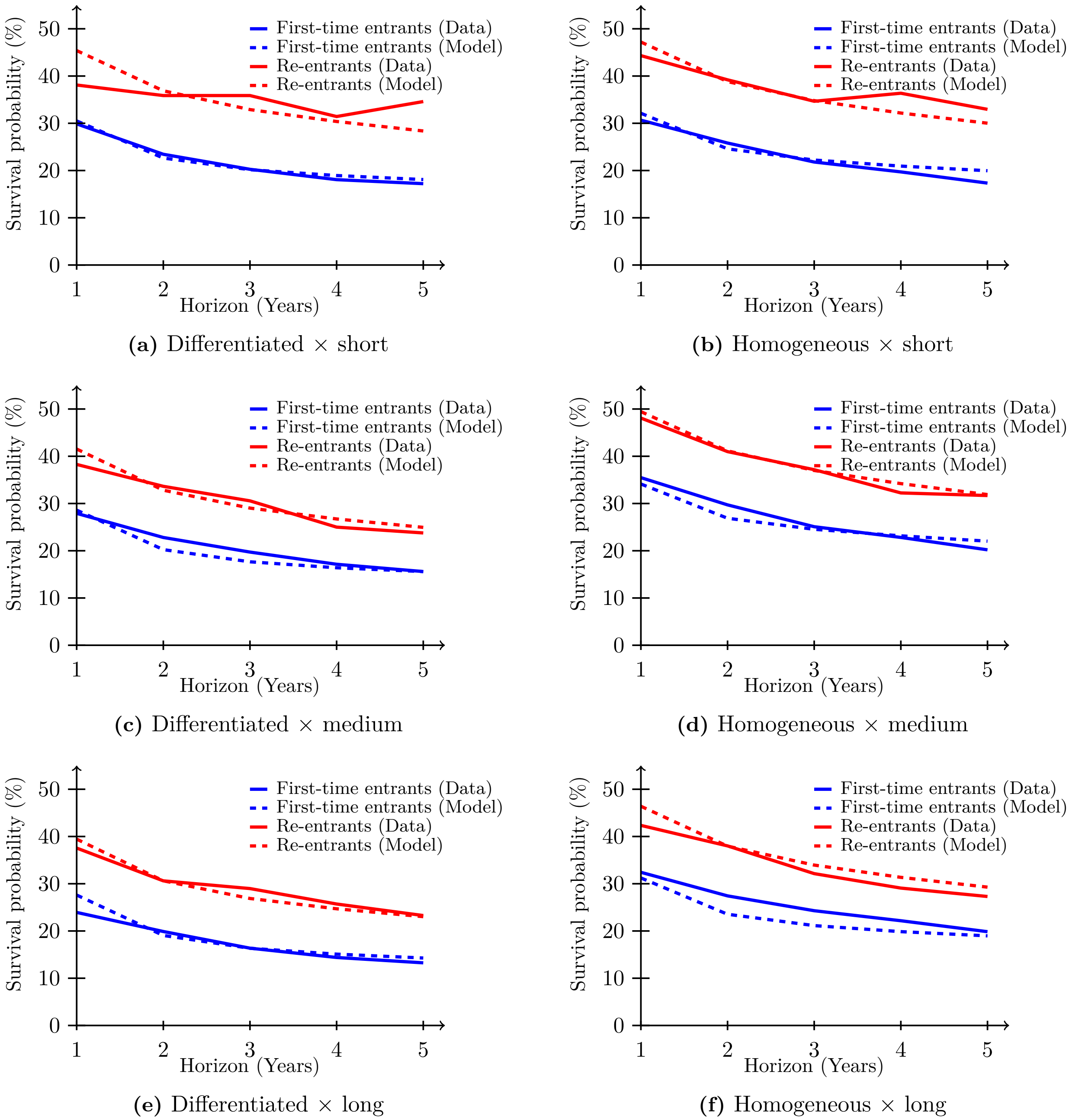


Figure H.3: Survival profiles by product type and distance

I A simple model with lumpy exports

Our continuous-time model has the advantage of facilitating time-aggregation corrections. However, since re-entry is pervasive and many exporters spend significant time close to the threshold, one may worry that (i) we may get in the model spurious entry and re-entry of firms that barely spent any time above the threshold and, (ii), this may exaggerate the intra-period extensive margin by including even very small intervals above the threshold for firms close to it. To address these concerns, we develop an extension of our model that introduces discrete shipments. This extension keeps all features of the original model except that firms can no longer export at every instant. Instead, firms receive an "export opportunity" shock with intensity $\eta > 0$. If there is no shock, then firms do not export and get zero instantaneous profits regardless of their potential profitability. If there is a shock, then firms decide whether to export or not. If they do, they obtain a discrete amount of export profits $\pi_i(\theta_t)$ if inexperienced and $\pi_e(\theta_t, \psi)$ if experienced:

$$\pi_i(\theta_t) = \frac{1}{\eta}\left\{ \begin{array}{c} \kappa\theta_t - F \text{ if export at } t \\ 0 \text{ otherwise} \end{array} \right\}$$
$$\pi_e(\theta_t; \psi) = \frac{1}{\eta}\left\{ \begin{array}{c} \psi\kappa\theta_t - F \text{ if export at } t \\ 0 \text{ otherwise} \end{array} \right\}.$$

We scale profits with η such that changing η does not change the average profits in a time period. The HJB equation of an inexperienced firm is, then,

$$rV = \underbrace{\eta^{-1}\left(\kappa\theta_t - F\right) + \eta^{-1}\lambda(\mathbb{E}V_e - V_i)}_{\text{profits conditional on exporting}} \qquad \underbrace{\eta dt}_{\text{probability of exporting}}$$
$$+ (\mu + \frac{1}{2}\sigma^2)\theta\frac{dV^1}{d\theta} + \frac{1}{2}\sigma^2\theta\frac{d^2V^1}{d\theta^2}\text{for}\kappa\theta > F$$
$$rV = (\mu + \frac{1}{2}\sigma^2)\theta\frac{dV}{d\theta} + \frac{1}{2}\sigma^2\theta\frac{d^2V}{d\theta^2}\text{for } \kappa\theta < F.$$

An analogous equation holds for the experienced firm. Since firms are risk neutral, η does not affect any value functions, hence, nor the threshold. However, it will affect the time of entry (it will now be above θ^*). It will also affect survival predictions: firms may not only exit because they are bad but also because they did not get lucky with the export opportunity shock. This matters more for firms close to the threshold. For reasonable values of η, firms that spend the entire period above the threshold are extremely likely to export.

I.1 Moments with $\eta < \infty$

Next, we compare the model predictions for different values of η. Note that a lower η tends to decrease survival probabilities: firms not only need to be above the threshold but also be hit by the export-opportunity shock to survive.[49] For this reason, we re-estimate the model for each value of η. We consider $\eta \in \{0.005, 0.01, 0.025, 0.05\}$, implying that if firms are above the threshold for an entire year, the expected number of shipments are 5, 10, 25, and 50, respectively. The average number of shipments by first-time entrants is 12.5 in the data, but this presumably includes firms that only spend a fraction of the time above the threshold. Conditioning on firms that survived for five years and looking at their average number of shipments in year 3 of their export experience yields 25.8 shipments.

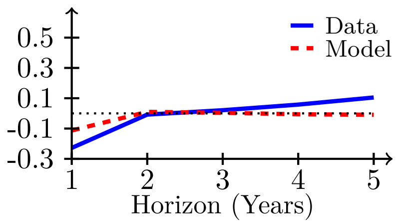
Panels A and B in Table I.1 show the estimated values for $\{\mu, \sigma, \lambda, \alpha\}$ and predicted survival probabilities, respectively, for different values of η. Clearly, η is not identified by survival moments: as we change η, the remaining parameters change to deliver the same survival probabilities. In other words, adding lumpiness does not hurt or improve the model's performance to match survival moments.

As argued before, η is also very important for the intra-period extensive margin and the growth-rates implications. For this reason, we replicate Figure 11 at our preferred value: $\eta = 0.025$. The model fit for shipments (panel B) is substantially improved. In particular, the standard deviation is much closer to that in the data. As a result, however, the overall volatility of sales (panel A) is now smaller than in the data, suggesting that other forces may increase the variance of small and young firms, e.g. marketing costs (Arkolakis, 2016).

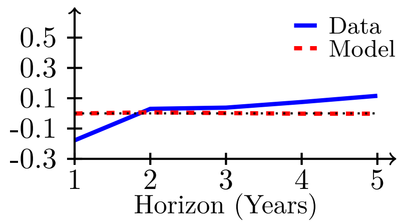
[49] There is a countervailing force: firms enter above the threshold and, therefore, are more likely to be above the threshold in the future. We find this effect to be weaker in our simulations.

Table I.1: SMM Estimation results

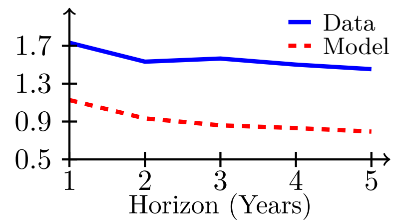
	Fixed parameters				
r	0.1	0.1	0.1	0.1	
η	0.005	0.01	0.025	0.05	
	Estimated parameters				
μ	-0.014	-0.014	-0.013	-0.010	
σ	0.052	0.052	0.053	0.052	
λ	1.435	1.938	2.301	2.336	
α	5.964	7.069	7.475	6.814	
	Survival probabilities				
	Panel A: First-time entrants				
	Model				Data
Year 1	0.300	0.295	0.300	0.304	0.294
Year 2	0.228	0.224	0.223	0.217	0.242
Year 3	0.202	0.200	0.199	0.193	0.208
Year 4	0.187	0.186	0.186	0.181	0.185
Year 5	0.177	0.176	0.176	0.174	0.169
	Panel B: Re-entrants				
	Model				Data
Year 1	0.432	0.438	0.444	0.439	0.405
Year 2	0.358	0.361	0.364	0.356	0.357
Year 3	0.313	0.316	0.324	0.317	0.329
Year 4	0.289	0.286	0.296	0.296	0.290
Year 5	0.269	0.268	0.276	0.278	0.282



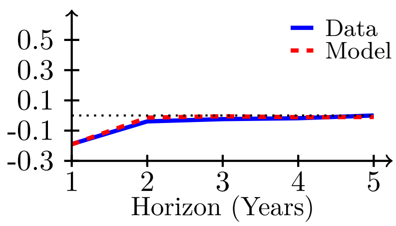
(a) Uncond. sales growth rate: Mean



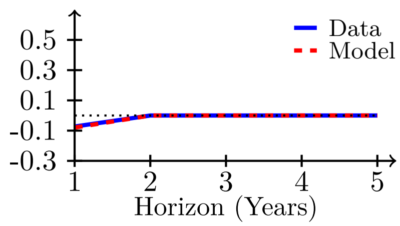
(b) Uncond. sales growth rate: Median



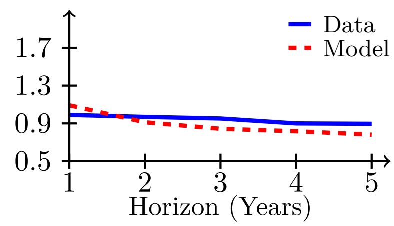
(c) Uncond. sales growth rate: Standard deviation



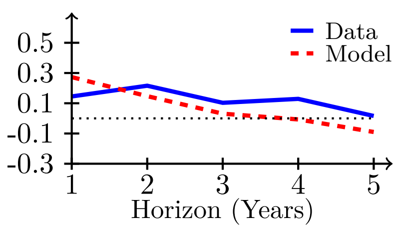
(d) Uncond. shipment growth rate: Mean



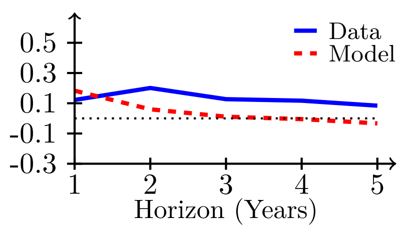
(e) Uncond. shipment growth rate: Median



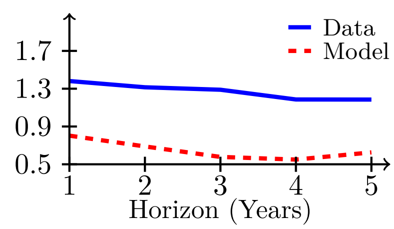
(f) Uncond. shipment growth rate: Standard deviation



(g) Sales growth rates cond. on surviving until year 5 (entry: year 0): Mean



(h) Sales growth rates cond. on surviving until year 5 (entry: year 0): Median



(i) Sales growth rates cond. on surviving until year 5 (entry: year 0): Standard deviation

Figure I.1: Other moments: Growth rates ($\eta = 0.025$)

J Sales by spell duration

In this section, we follow Fitzgerald et al. (2024) and present facts related to firm sales depending on the duration of an export spell. More specifically, we take our first-time entrants and define a dummy $\mathbf{1}_s$ that is equal to one if the firm's export experience (i.e. without any exits in between) lasts for exactly $s \in \{1, \ldots, 5, 6\}$ periods.[50] Then, we run a regression of $\ln(\text{sales}_t)$ on these dummies, with the one-year spells being the base group. Thus, each coefficient has the interpretation of how much more a firm of spell s exports in horizon h relative to the sales of a firm that did not survive any periods. We consider specifications adding destination-year, product, and firm-year fixed effects.

Table J.1: Log(sales)

	(1)	(2)	(3)
Year 0, 1-year spell	-	-	-
Year 0, 2-year spell	1.188***	1.087***	0.933***
	(0.05406)	(0.04841)	(0.06374)
Year 1, 2-year spell	0.600***	0.544***	0.486***
	(0.05206)	(0.04808)	(0.06810)
Year 0, 3-year spell	1.680***	1.629***	1.296***
	(0.07170)	(0.06416)	(0.07978)
Year 1, 3-year spell	1.421***	1.376***	1.247***
	(0.07403)	(0.06790)	(0.08651)
Year 2, 3-year spell	0.976***	0.945***	0.965***
	(0.07428)	(0.07326)	(0.09980)
Year 0, 4-year spell	1.946***	1.762***	1.380***
	(0.09558)	(0.08397)	(0.10314)
Year 1, 4-year spell	1.930***	1.784***	1.574***
	(0.09518)	(0.08418)	(0.10308)
Year 2, 4-year spell	1.901***	1.739***	1.542***
	(0.09770)	(0.08696)	(0.10631)
Year 3, 4-year spell	1.310***	1.180***	1.043***
	(0.09570)	(0.09406)	(0.14098)
Year 0, 5-year spell	1.948***	1.786***	1.388***
	(0.11755)	(0.10269)	(0.14160)
Year 1, 5-year spell	1.867***	1.742***	1.415***
	(0.12117)	(0.11184)	(0.14746)
Year 2, 5-year spell	2.089***	1.969***	1.837***
	(0.11423)	(0.10403)	(0.13085)
Year 3, 5-year spell	2.017***	1.892***	1.913***

[50] Firms that survive 7 or more years are excluded from the regression. We also exclude right-censored export spells, i.e. those where we cannot determine how many years they survived.

	(1)	(2)	(3)
	(0.11448)	(0.11055)	(0.14735)
Year 4, 5-year spell	1.414***	1.294***	1.433***
	(0.11272)	(0.12025)	(0.18809)
Year 0, 6-year spell	2.494***	2.237***	1.973***
	(0.15069)	(0.12603)	(0.15077)
Year 1, 6-year spell	2.441***	2.257***	2.068***
	(0.14140)	(0.11892)	(0.14011)
Year 2, 6-year spell	2.485***	2.332***	2.192***
	(0.14839)	(0.12869)	(0.14925)
Year 3, 6-year spell	2.478***	2.343***	2.278***
	(0.14900)	(0.14303)	(0.18870)
Year 4, 6-year spell	2.471***	2.257***	2.350***
	(0.13792)	(0.14222)	(0.21873)
Year 5, 6-year spell	1.877***	1.673***	1.674***
	(0.13311)	(0.15086)	(0.23673)
Destination-year fixed effect	No	Yes	Yes
Product fixed effect	No	Yes	Yes
Firm-year fixed effect	No	No	Yes
Observations	33675	33398	19288
R^2	0.104	0.316	0.683

Table J.1 shows the results. Overall, we see that firms that survive longer sell more, but that their sales are relatively flat over the life-cycle, except for the last year, where they sell substantially less - likely an artifact of time-aggregation (i.e. during the last period, firms exit, so that year is shorter). This result is robust across all specifications; only the levels of sales seem to be affected by the fixed effects. Figure J.1 plots the results in the case with product and destination-year fixed effects activated, as well as the model predictions under the assumptions of CES demand and equal κ and F (which is required to compare sales levels across firms with different spell durations). As argued in the main text, because of selection, the model predicts strong growth in the beginning, which is counterfactual, and a large drop in the exit year due to a partial-year effect upon exit. The former is not present in the data, suggesting that even profitable firms find it difficult to increase sales, even after learning they are very profitable in that market.

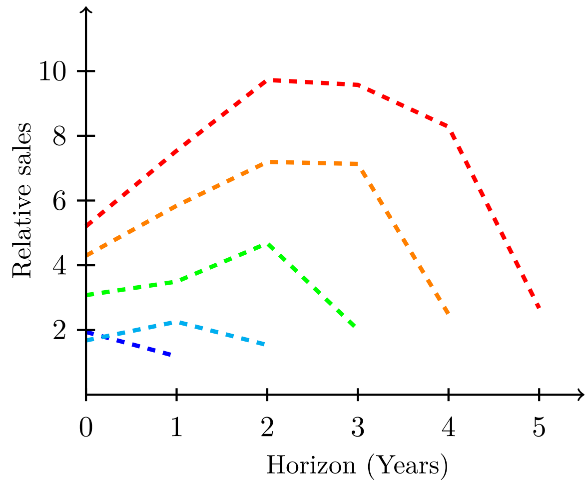
Table J.2: Log(sales) (Annual data)

	(1)	(2)	(3)
Year 0, 1-year spell			
Year 0, 2-year spell	0.865***	0.804***	0.628***
	(0.04197)	(0.03857)	(0.05481)
Year 1, 2-year spell	0.840***	0.801***	0.678***

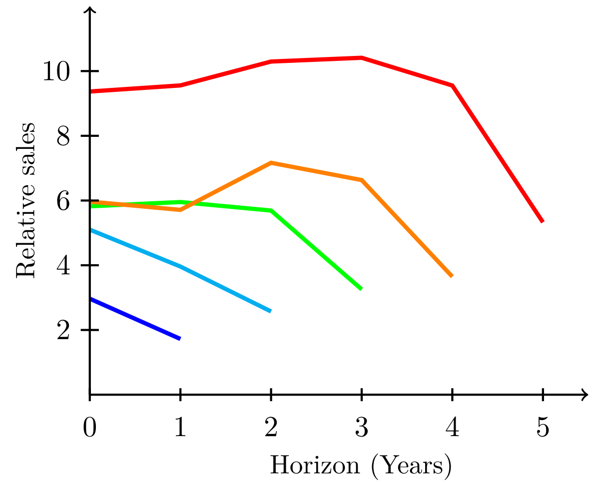
	(0.04097)	(0.03998)	(0.05331)
Year 0, 3-year spell	1.212***	1.109***	0.963***
	(0.06014)	(0.05507)	(0.07117)
Year 1, 3-year spell	1.623***	1.531***	1.454***
	(0.06201)	(0.05889)	(0.07096)
Year 2, 3-year spell	1.109***	1.029***	1.014***
	(0.06276)	(0.06377)	(0.08483)
Year 0, 4-year spell	1.354***	1.274***	1.177***
	(0.08083)	(0.07069)	(0.09086)
Year 1, 4-year spell	1.898***	1.813***	1.699***
	(0.08365)	(0.07605)	(0.09549)
Year 2, 4-year spell	1.968***	1.904***	1.868***
	(0.08478)	(0.07615)	(0.10065)
Year 3, 4-year spell	1.396***	1.318***	1.392***
	(0.08654)	(0.08369)	(0.12019)
Year 0, 5-year spell	1.531***	1.400***	1.172***
	(0.08971)	(0.08422)	(0.10630)
Year 1, 5-year spell	2.234***	2.126***	1.994***
	(0.08785)	(0.07815)	(0.09658)
Year 2, 5-year spell	2.239***	2.137***	2.150***
	(0.10243)	(0.09674)	(0.12765)
Year 3, 5-year spell	2.230***	2.123***	1.950***
	(0.09875)	(0.09764)	(0.13641)
Year 4, 5-year spell	1.636***	1.549***	1.616***
	(0.09841)	(0.10230)	(0.19776)
Year 0, 6-year spell	1.934***	1.703***	1.606***
	(0.13314)	(0.10588)	(0.13468)
Year 1, 6-year spell	2.425***	2.246***	2.084***
	(0.12744)	(0.10968)	(0.14593)
Year 2, 6-year spell	2.569***	2.428***	2.349***
	(0.12062)	(0.10763)	(0.13471)
Year 3, 6-year spell	2.472***	2.306***	2.172***
	(0.12339)	(0.11891)	(0.14650)
Year 4, 6-year spell	2.341***	2.185***	2.421***
	(0.12505)	(0.12319)	(0.16818)
Year 5, 6-year spell	1.833***	1.704***	1.997***
	(0.13266)	(0.12993)	(0.21339)
Destination-year fixed effect	No	Yes	Yes
Product fixed effect	No	Yes	Yes
Firm-year fixed effect	No	No	Yes

Observations	42783	42476	25013
R^2	0.099	0.299	0.673

We repeat the exercise with annual data based on calendar years, as in the original analysis of Fitzgerald et al. (2024) (Table J.2). Figure J.2 shows that the fit looks better: now the data also exhibits a hump, which is also a feature in our model. The difference between the results with annual data and firm-market-specific years suggests that the partial-year effect entirely drives the hump. As discussed before, our uniform-entry and pure continuous-time model seems to overcorrect for this partial-year effect, leading to an exacerbated growth rate between the first two years of the export experience.



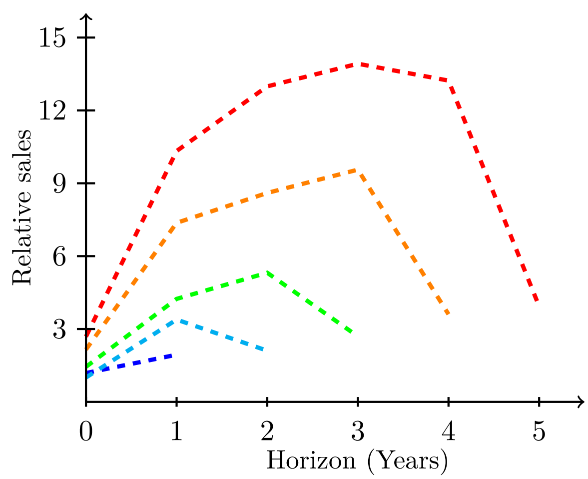
(a) Sales by export spell, model



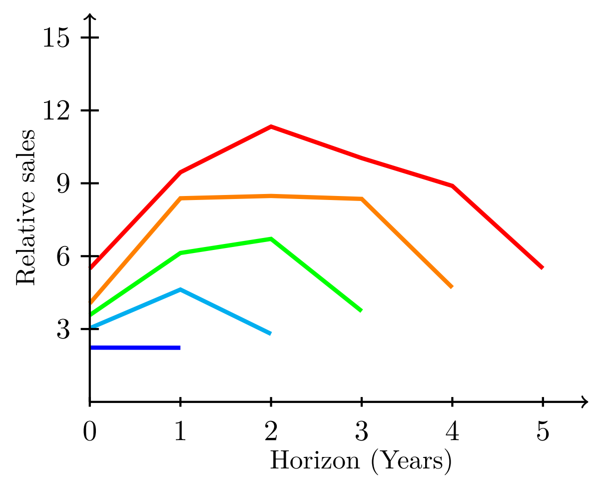
(b) Sales by export spell, data

Figure J.1: Sales by export spell, model vs. data

Notes: To construct the model predictions, we first classify first-time entrants according to the length of their export spell, i.e. the number of firm-specific years of uninterrupted exports. We compute the mean log sales in each year of their export experience, conditional on being a firm that survives for exactly $x \in \{1, 2, 3, 4, 5, 6\}$ years. We then plot these average sales in levels for firms that last for $x = 2$ (blue), $x = 3$ (cyan), $x = 4$ (green), $x = 5$ (orange) and $x = 6$ (red) divided by the average sales in levels of firms that do not export after the entry year.



(a) Sales by export spell, model



(b) Sales by export spell, data

Figure J.2: Sales by export spell, model vs. data (Annual data)

Notes: To construct the model predictions, we first classify first-time entrants according to the length of their export spell, i.e. the number of calendar years of uninterrupted exports. We compute the mean log sales in each year of their export experience, conditional on being a firm that survives for exactly $x \in \{1, 2, 3, 4, 5, 6\}$ years. We then plot these average sales in levels for firms that last for $x = 2$ (blue), $x = 3$ (cyan), $x = 4$ (green), $x = 5$ (orange) and $x = 6$ (red) divided by the average sales in levels of firms that do not export after the entry year.